Fuzzy based Computing for Disabled using 3D Head Movement

Pradeep V
Alva's Institute of Engineering & Technology, Moodbidri, DK, Karnataka, India
E-mail: writetopv@gmail.com

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For those with disabilities in the movement who have not yet had a fair chance to use the typical input devices of a personal computer, many authors have put forth replacements for the mouse during the past three decades. The overhead of employing head-mounted devices is decreased in camera-based systems by using the web camera as the mouse. The research problems and opportunities are tracking the user's facial expression of various users with various head poses through the camera and accurately converting into mouse cursor movement and click events. The usual GUI interactive features like menus and scroll bars that need horizontal or vertical movement are difficult to operate on the existing systems since they can only move the cursor in a slanting manner. Unintentional head movements by users frequently result in the current system losing track of facial feature tracking. The proposed system uses a standard web camera to capture the three-dimensional head rotation. To shift the mouse pointer vertically, the positions of the nasal bridge and nose tip are collected. The inner corners of the left and right eyes, as well as the tip of the nose, are also used to shift the mouse cursor horizontally. Unintentional head motions are disregarded to prevent the loss of face features, and by using fuzzy logic, the movement of the mouse pointer is only mapped with the intended head movements. The fuzzy control uses the head's rate, direction, and distance as inputs to determine how the mouse pointer will travel. By capturing the stable, purposeful, and sudden movements of the head, respectively, the fuzzy system classifies the movement of the head as weak, fair, or powerful. By removing the weak and strong head motions, the algorithm just maps the fair head movements with cursor movement on the screen. The proposed system has achieved the horizontal and vertical movement of the cursor and the results are significant when compared with the existing system. The system also successfully ignores the slight movement of the head captured by the web camera when the user remains the head stable, and the feature loss is completely avoided.

Povzetek: Predstavljen je sistem za invalide brez rok, ki uporablja 3D premike glave in logiko mehkih množic. Sistem zaznava premike glave s spletno kamero in jih pretvarja v premike miške, pri čemer izloča nenamerne premike glave.

1 Introduction

As per the World Report on Disability 2011 by World Health Organization Census, around one billion people are suffering from some type of disability and around 110 million persons have extremely major difficulties in functioning such as quadriplegia [1]. In India, around 2.68 Cr persons are suffering from a disability and around 5.4 million people have a disability in movement [2]. Assistive technology facilitates people with disabilities to enhance productivity and live independently and plays a vital role in accomplishing the equalization of chances for disabled persons [3]. They may utilize hands-free computing significant in their daily lives that can range from using the movement of the head, tongue, lips, or mouth to voice-enabled interfaces utilizing a microphone and speech recognition software or Bluetooth technology [4]. Computer vision can be used in applications that require visual searches by performing detailed image analysis and solving more complex problems such as facial recognition [5]. The method proposed by Paul Viola and Michael Jones [6] is a prevalent approach for real-time face detection that is dependent on Haar features represented by edges and lines that allow capturing important elements in the face such as the mouth or nose. The facial analysis algorithm proposed by Kazemi and Sullivan [7] plays a primary role in the image processing techniques in which the key feature is facial landmarks. Fuzzy logic is a powerful technique that can be implemented in many applications to express values that are uncertain in nature by defining the amount of degree to which an item fits into a particular set [8]. The proposed system enhances the capability of controlling the mouse cursor through the camera-based hands-free computing systems that enable people with disability in the movement to use a standard personal computer by attaining the horizontal and vertical movement of the mouse cursor by capturing the 3D movement of the users' head and mapping the mouse cursor movement only with the intentional head movement of the user by applying fuzzy logic in decision-making.

2 Previous work

Various hands-free mouse replacement systems have been developed and many improvements have been witnessed during the past three decades. Some applications

were designed that were used only for limited and specific applications [9]. Few solutions depend on special software and hardware that are specifically designed for people with some form of disability in the movement [10]. Many applications developed for replacing mouse use hardware systems with high-cost [11]. Most of such applications require specially designed hardware to facilitate the motor disabled to use the computer by generally wearing on the head or face [12-26]. To condense the burden of using a hardware system with huge cost and holding on to the head, the head motions of the user are captured with a camera for controlling the mouse cursor of the computer [27-41]. Many systems use speech recognition to map the mouse click events as it is a straightforward and user-friendly interface. The current applications facilitate the disabled users to move the cursor comfortably only in a slanting direction, and so find it difficult to use the common graphical interactive features such as menus and scroll bars that require the cursor to move horizontally or vertically [42-44]. Synchronizing the speed of movement between the mouse cursor and the user's head is very difficult [45-51]. They lose the tracking of facial features when the user unintentionally moves the head [52-53]. They fail to capture the feature due to different illumination [54] [55]. Occlusions, limited head movements, and variant poses are the major problems in tracking facial features [56] [57]. Participants were irritated by slight cursor changes when the cursor entered the target and the participant tried to continue gazing at the target [58]. Several developments need to be made for the head-mounted technology to continue to replace the actual mouse. The eye gaze motions have been monitored through solutions to manipulate the mouse pointer on the screen. To lessen the expense of employing expensive hardware limited options for system and head-mounted gadgets employ web cameras to record user head movements in order to utilize mouse pointer controls like. Naturally, People gaze at the thing they want to do something with. Consequently, little work is done on moving the mouse cursor. Utilizing eye movement to increase effectiveness monitoring the movement of the head and other parts of the head or a situation like [59 - 67].

The research challenges have paved the approach to identify future guidelines for research and development such as moving the cursor horizontally or vertically, synchronizing the mouse cursor with the head movement, avoiding feature loss, and overcoming the limitation of environment control.

3 Methodology

Fuzzy logic is used in the proposed system's decision-making to simplify and increase the effectiveness of controlling the cursor and its interactions on graphical user interfaces, allowing "mobility-impaired" individuals—those who are unable to move the mouse or any pointing device—to use computers conveniently and easily. The head movement takes the place of mouse movements, and the camera records eye blinks. The mouse cursor is moved by head movement, left eye blinks in place of left mouse clicks, and right eye blinks in place of right mouse clicks. The suggested system's initial function is to take a picture of the user's nose. The distance, direction, and rate of head movement all contribute to the fuzzy input variations for head movement detection, whereas period and interval only contribute to the fuzzy input variations for nose direction. The cursor movement and mouse clicks will be affected by the fuzzy logic we employ to integrate the aforementioned input variations. Head and nasal movements can be predictable and unexpected.

4.2 The Region of interest (ROI)

The proposed system uses a web camera to record the video sequences of the user's head movement. Though the web camera captures the sequence of images in two-dimensional, the proposed system calculates the users' head movement in three-dimensional. To detect the face region, the system uses the algorithm designed by Viola and Jones [6] known as the Haar Cascade object detection algorithm using OpenCV. To estimate the Region of Interest (ROI), the proposed system uses the algorithm designed by Kazemi and Sullivan [7] known as a pre-trained facial landmark detector using DLib built-in library. The Inner-left-eye-corner, the Inner-right-eye-corner, the Nose-bridge, and the Nose-tip are the proposed system's ROIs.

4.3 Fuzzy logic for mapping intentional head movement

To avoid the loss of facial features, the proposed system ignores unintentional head movements and maps the movement of the mouse cursor only with the intentional movements of the head by applying fuzzy logic. Tracking the movement of users' heads is an imprecise computational task where the tolerance for imprecision has to be exploited for choosing the best outcomes and making complex decisions by applying soft computing techniques. Head movement is a physiological occurrence of imprecision and so fuzzy logic can be applied to make a computer resolve the direction, the distance, and the rate of movement of the head [68]. The fuzzy control system takes the 'Distance', 'Direction', and 'Rate' of the head movements as inputs for controlling the mouse cursor movement.

4.4 ‘Distance’ of head movement

Capturing the 3D vertical movement of the head

Capturing the user's head's vertical movement in three-dimensional is achieved by extracting the nose bridge and nose-tip points from the facial landmark. The mouse cursor's movement in the vertical direction is achieved when the user lifts and bends the head in the vertical direction. The distance between the nose-bridge and nose-tip points increases when the user bends the head down. The distance in head movement is captured and that determines the distance of the mouse cursor movement in the vertical direction towards the bottom. Similarly, the distance between the nose-bridge and nose-tip points decreases when the user lifts the head up.

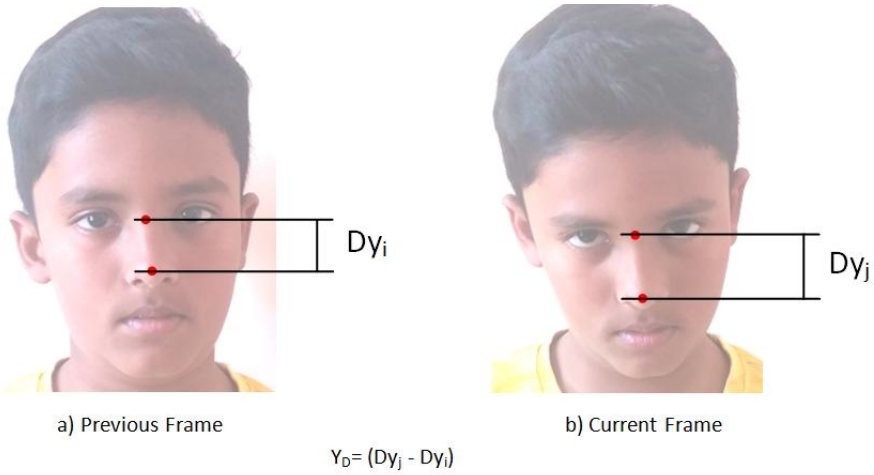


Figure 1: Capturing the vertical distance of the head movement.

The distance in head movement is captured and that determines the distance of the mouse cursor movement in the vertical direction upwards. When the user lifts the head upwards, the distance between the nose bridge and the nose tip will be gradually decreasing when captured by the camera, facing the user. Similarly, when the user bows the head downwards, the distance between the nose bridge and the nose tip will be gradually increasing when captured by the camera. The distance of the head movement in the vertical direction, YD, is the difference in the distance between the nose bridge and the nose tip captured by the previous frame and the current frame as shown in Fig. 1.

Capturing the 3D horizontal movement of the head

Capturing the user's head's horizontal movement in three-dimensional is achieved by extracting the inner-left-eye-corner, nose-tip, and inner-right-eye-corner points from the facial landmark. The mouse cursor's movement in the horizontal direction is achieved when the user turns the head left or right in the horizontal direction. The distance between the nose-tip and inner-right-eye-corner point's increases and the distance between the inner-left-eye-corner and nose-tip points decreases when the user turns the head left. The distance in head movement is captured and that determines the distance of the mouse cursor movement in the horizontal direction towards the left. Similarly, the distance between the nose-tip and inner-right-eye-corner points decreases, and the distance between the inner-left-eye-corner and nose-tip points increase when the user turns the head right. The distance in head movement is captured and that determines the distance of the mouse cursor movement in the horizontal direction towards the right. The distance of the head movement in the horizontal direction is (XD1, XD2), where XD1 is the difference in the distance between the inner left eye corner and the nose tip captured by the previous frame and the current frame and XD2 is the difference in the distance between the nose tip and the inner right eye corner captured by the previous frame and the current frame and shown in Fig. 2.

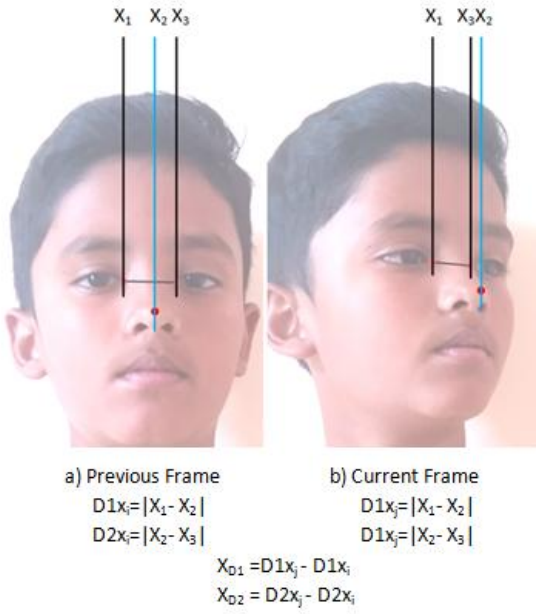


Figure 2: Capturing the horizontal distance of the head movement.

4.5 'Direction' of the head movement

If the value of Y_D is negative, then the direction of the head movement is 'north' and the direction is 'south', if positive. Similarly, if the value of X_{D1} is negative or the value of X_{D2} is positive, then the direction is 'west' and the direction is 'east' for a positive X_{D1} value or negative X_{D2} value.

Table 1: Direction vs Distance of the head movement.

Direction	Distance		
	Y_D	X_{D1}	X_{D2}
Null	Null	null	Null
North	Negative	null	Null
South	Positive	null	Null
West	Null	negative	positive
East	Null	positive	negative
north-east	Negative	positive	negative
north-west	Negative	negative	positive
south-east	Positive	positive	negative
south-west	Negative	negative	positive

The combinations of values of YD and XD1 or XD2 are denoted as any one of the directions: southeast, northeast, southwest, or northwest. Otherwise, the Direction is 'null' as shown in Table 1.

4.6 'Rate' of the head movement

If the value of ($|Y_D|$, $|X_{D1}|$, $|X_{D2}|$) is below the minimum threshold, then the rate of head movement is 'low'. Similarly, the rate is 'high' when the value is above the maximum threshold and otherwise, 'moderate'.

4.7 Fuzzification

The fuzzy system uses the following linguistic variables: *Variation_x, Variation_y, Strength,* and *Output*. These linguistic variables use the following set of decompositions where each member is known as the linguistic term.

Variation_x = {Null, Positive, Negative}
Variation_y = {Null, Positive, Negative}
Strength = {Weak, Fair, Strong}
Output = {Null, Fair_N, Fair_S, Fair_W, Fair_E, Fair_NE, Fair_NW, Fair_SE, Fair_SW}

The relationships among *Variation_x, Variation_y* and *Direction* are shown in Table 2, where *Variation_x, Variation_y* are the linguistic variables, and *Direction* is the input generated from the head movement.

Table 2: Variation vs direction of the head movement in x and y axes

Variation_x	Variation_y	Direction
Null	Null	Null
Null	Negative	North
Null	Positive	South
Negative	Null	West
Positive	Null	East
Positive	Negative	north-east
Negative	Negative	north-west
Positive	Positive	south-east
Negative	Positive	south-west

The value of *Strength* is based on *Rate* as shown in Table 3, where *Strength* is the linguistic variable and *Rate* is the input generated from the head movement.

Table 3: Strength vs. rate of the head movement.

Rate		Strength
x-axis	y-axis	
low	Weak	low
low	Fair	moderate
low	Strong	high
moderate	Fair	low

moderate	Fair	moderate
moderate	Strong	high
high	Strong	low
high	Strong	moderate
high	Strong	high

The linguistic terms of the linguistic variable 'Strength' give the following denotations:

- 'Weak': denotes the head is stable, but the camera has captured slight movement.
- 'Fair': denotes the intentional head movement; the user has moved the head intentionally to move the cursor in the window screen.
- 'Strong': denotes the sudden movement of the head; the user's casual head movement such as turning back, and bending head to pick something.

The linguistic terms of the linguistic variable 'Output' are set as shown in Table 4. The linguistic term 'Null' of the linguistic variable 'Output' assures that the user's head movement is not intentional.

Table 4: Output vs. Strength and direction of the head movement.

Strength	**Direction**	**Output**
Weak	-	Null
Strong	-	Null
Fair	Null	Null
Fair	North	Fair_N
Fair	South	Fair_S
Fair	West	Fair_W
Fair	East	Fair_E
Fair	North-East	Fair_NE
Fair	North-West	Fair_NW
Fair	South-East	Fair_SE
Fair	South-West	Fair_SW

4.8 Defuzzification

Table 5: Output vs defuzzification variables.

Output	**A**	**B**
Fair_N	0	$-\|Y_D\|$
Fair_S	0	$\|Y_D\|$
Fair_W	$-(\max(\|X_{D1}\|, \|X_{D2}\|))$	0
Fair_E	$\max(\|X_{D1}\|, \|X_{D2}\|)$	0
Fair_NE	$\max(\|X_{D1}\|, \|X_{D2}\|)$	$-\|Y_D\|$
Fair_NW	$-(\max(\|X_{D1}\|, \|X_{D2}\|))$	$-\|Y_D\|$
Fair_SE	$\max(\|X_{D1}\|, \|X_{D2}\|)$	$\|Y_D\|$
Fair_SW	$-(\max(\|X_{D1}\|, \|X_{D2}\|))$	$\|Y_D\|$

The defuzzification for *Output*, the linguistic variable is set as below:

IF Output = Null, THEN
Current_Cursor_Position (X_c, Y_c) = *Previous_Cursor_Position* (X_p, Y_p) ;
ELSE
Current_Cursor_Position (X_c, Y_c) = *Previous_Cursor_Position* $(X_p + A*nx, Y_p + B*ny)$;

The values of the variables A and B are shown in Table 5, which are based on the value of the linguistic variable 'Output'. 'nx' and 'ny' are the factors that determine the rate of the cursor movement in the window pertaining to the rate of the intentional head movement.

5 Results and discussion

The laptop computer's configuration for testing the system is as follows:
- 2.10 GHz Intel Pentium CPU B950 with 2 GB of RAM
- 1366 x 768 screen resolution with landscape orientation
- Windows 7 Professional 32-bit operating system
- Logitech C170 webcam
- OpenCV 2.1.0

5.1 Attaining the horizontal movement of the mouse cursor

The horizontal movement of the head, i.e., turning the head left or right, controls the movement of the mouse cursor in the horizontal direction. To attain the horizontal movement of the mouse cursor, the cursor's vertical movement should be minimum. The attainment of the cursor's horizontal movement is measured by capturing the variation in the vertical direction in the consecutive frames. The experiment is done with the 10 users intentionally moving the cursor in the horizontal direction from the left end to the right end of the screen. The initial variation is chosen eliminating the negligible variations in the beginning. The vertical variation in the *i*th frame for user *k* is $Y_{ki} - Y_{k0}$, where (X_{k0}, Y_{k0}) is the cursor position in the initial frame for user k and (X_{ki}, Y_{ki}) is the *c*ursor position in the *i*th frame for user *k*.

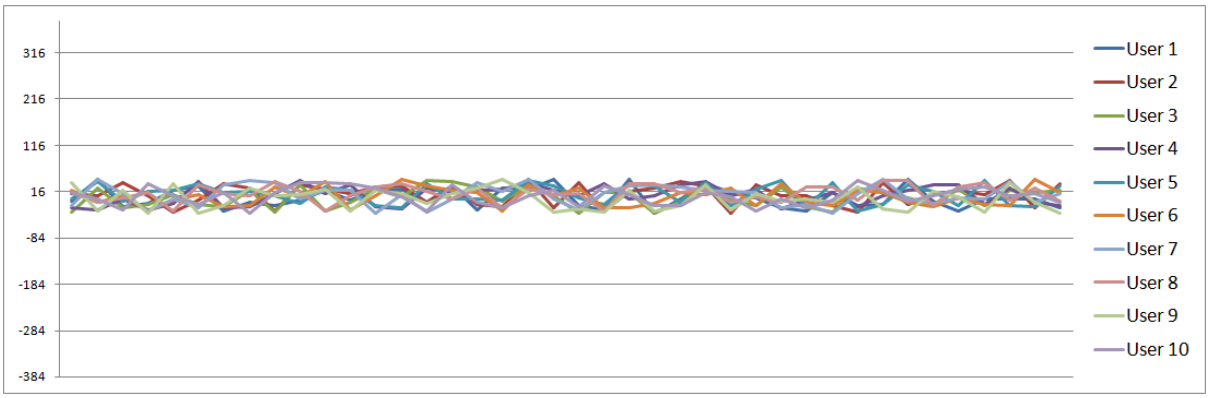


Figure 3: Vertical variations of the cursor during horizontal move in the proposed 3D method.

Fig. 3 shows the graph of the variation in pixels in the vertical direction in the successive frames when the experiment is done with the proposed method of capturing the head rotation in three-dimensional for mouse cursor movement. For n users and m frames, the lower limit is calculated as $\min_{\substack{1\le k\le n\\1\le i\le m}}(Y_{ki}-Y_{k0})$ and the upper limit as $\max_{\substack{1\le k\le n\\1\le i\le m}}(Y_{ki}-Y_{k0})$.The upper and lower limit of the variations in pixels is found as 42 and -31 pixels on average with the 3D method. When the experiment is done with the existing method of capturing the two-dimensional head rotation, the upper and lower limit of the variations in pixels is found as 87 and -76 pixels on average as shown in Fig. 4.

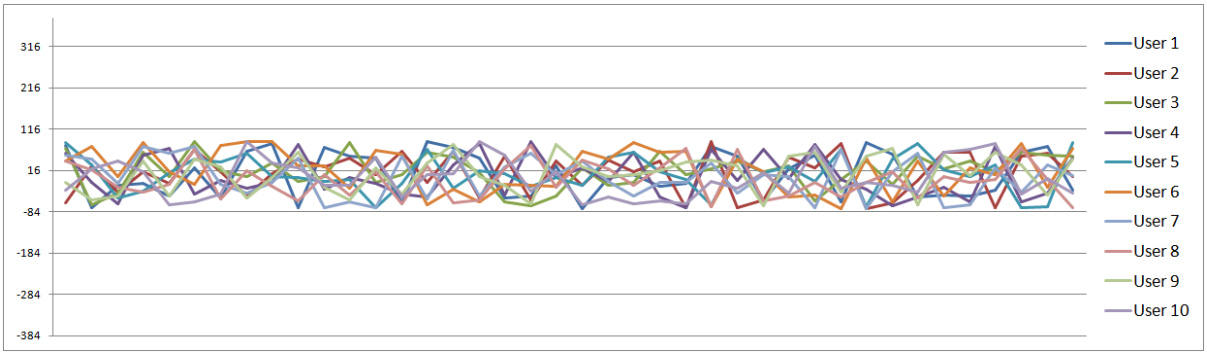


Figure 4: Vertical variations of the cursor during horizontal move in the existing 2D method.

With the tolerance of T_p pixels of variation, the success rate of moving the mouse cursor in the horizontal direction is calculated as

$$SR = \frac{SC}{m.n}$$

where, SC is the success count that is calculated as

$$SC = \sum_{j=1}^{m.n}\left(1_{[S_j=1]}\right)$$

where S_j is the success array that takes the following values.

$$S_j = \begin{cases} 1, & if\ (Y_{ki}-Y_{k0}) \le T_p \\ 0, & Otherwise \end{cases}, 1 \le j \le m.n,\ \ 1 \le k \le n, 1 \le i \le m$$

Table 6: Attainment of horizontal cursor movement

Variations in pixels				Tolerance	Success rate		
Lower limit		Upper limit					
Existing system	Proposed system	Existing system	Proposed system	±30 pixels of variation	Existing system	Proposed system	Improvement
-76	-31	87	42		37%	82%	71.4%

Table 6 shows the attainment of horizontal movement where the data captured in the proposed 3D method is compared with the existing 2D method. With the tolerance of ±30 pixels of variation, the achieved success rate of moving the mouse cursor is 82% in the horizontal direction when capturing the head in three dimensional, comparing to 37% in the horizontal direction when capturing the head in two dimensional. The improvement in the success rate of moving the mouse cursor in the horizontal direction is calculated as $\frac{(SR_P - SR_E)}{1-SR_E} \times 100$, where $SR_P$and $SR_E$are the success rates of the proposed and existing system. In the above scenario, the improvement in the success rate of moving the mouse cursor in the horizontal direction is *71.4%*.

5.2 Attaining the vertical movement of the mouse cursor

The vertical movement of the head, i.e., lifting up or bending down the head, controls the movement of the mouse cursor in the vertical direction. To attain the vertical movement of the mouse cursor, the cursor's horizontal movement should be minimum. The attainment of the cursor's vertical movement is measured by capturing the variation in the horizontal direction in the consecutive frames. The experiment is done with the same 10 users intentionally moving the cursor in the vertical direction from the top to the bottom end of the screen by choosing the initial variation eliminating the negligible variations in the beginning. The horizontal variation in the *i*th frame for user *k* is $X_{ki} - X_{k0}$.

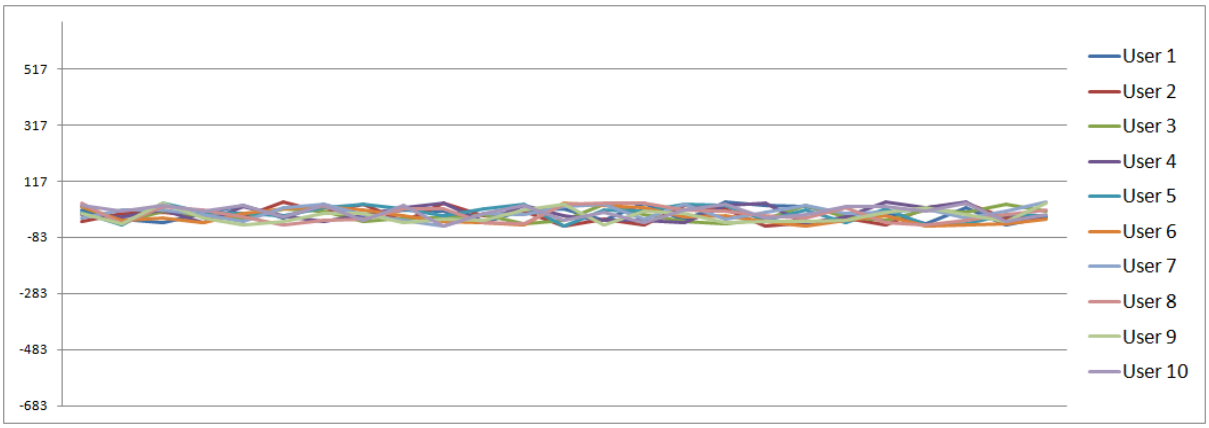


Figure 5: Horizontal variations of the cursor during vertical move in the proposed 3D method.

Fig. 5. shows the graph of the variation in pixels in the horizontal direction in the successive frames when the experiment is done with the proposed 3D method. For *n* users and *m* frames, the lower limit is calculated as $\min_{\substack{1\le k\le n\\1\le i\le m}}(X_{ki} - X_{k0})$ and the upper limit as $\max_{\substack{1\le k\le n\\1\le i\le m}}(X_{ki} - X_{k0})$.The upper and lower limit of the variations in pixels is found as 41 and -43 pixels on average with the 3D method. When the experiment is done with the existing 2D method, the upper and lower limit of the variations in pixels is found as 101 and -92 pixels on average as shown in Fig. 6.

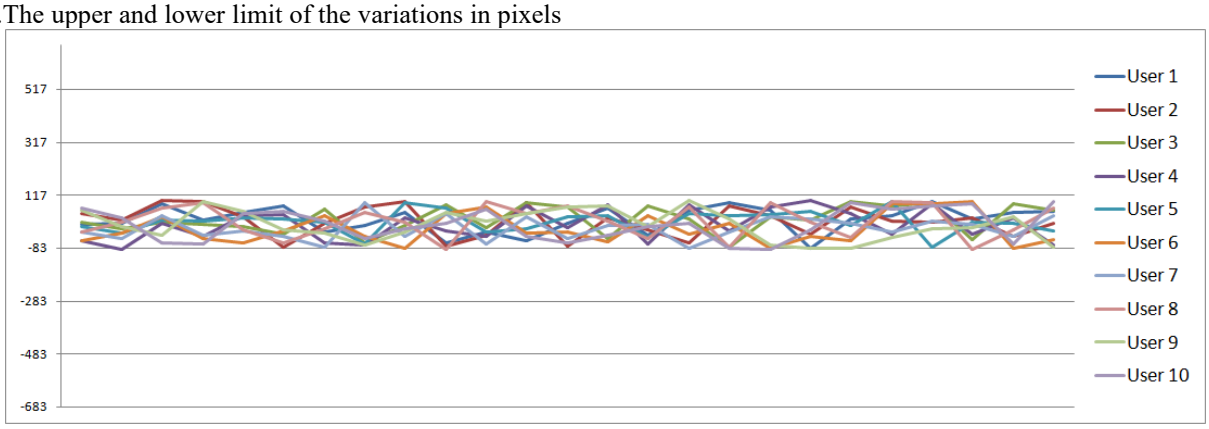


Figure 6: Horizontal variations of the cursor during vertical move in the existing 2D method.

The success rate of moving the mouse cursor in the vertical direction is calculated based on the following success array.

$$S_j = \begin{cases} 1, & if\ (X_{ki} - X_{k0}) \le T_p, 1 \le j \le m.n, 1 \le k \le n, 1 \le i \le m \\ 0, & Otherwise \end{cases}$$

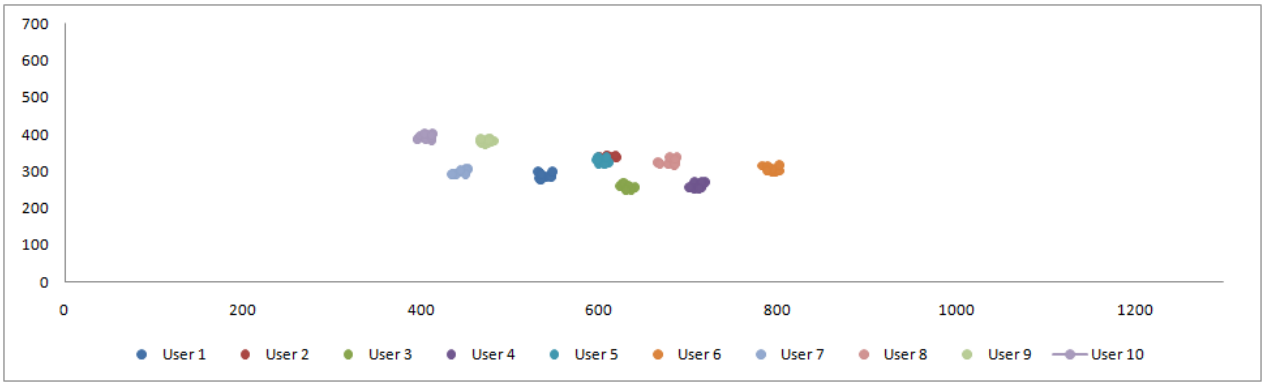
Table 7: Attainment of vertical cursor movement

Variations in pixels				Tolerance	Success rate		
Lower limit		Upper limit					
Existing system	Proposed system	Existing system	Proposed system	±30 pixels of variation	Existing system	Proposed system	Improvement
-92	-43	101	41		31%	71%	58%

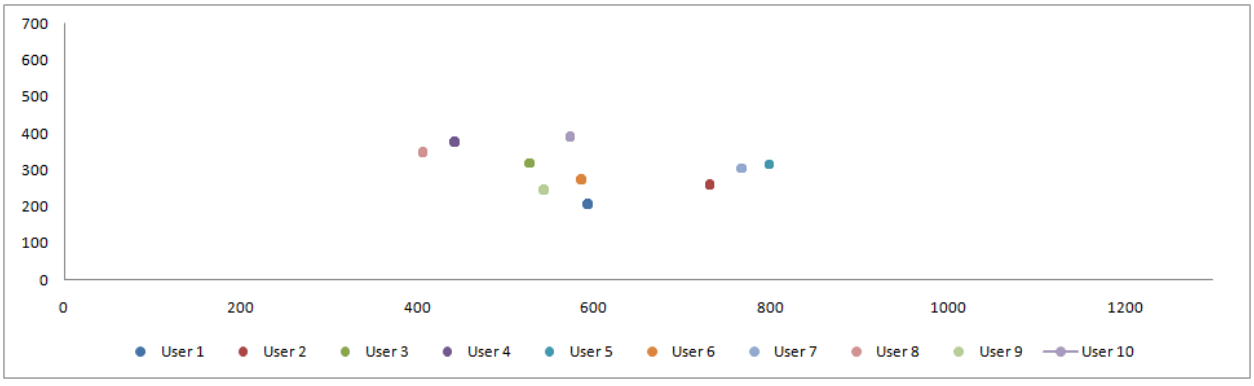
Table 7 shows the attainment of vertical movement where the data captured in the proposed 3D method is compared with the existing 2D method. With the tolerance of ±30 pixels of variation, the achieved success rate of moving the mouse cursor is 71% in the vertical direction when capturing the head in three dimensional, compared to 37% in the vertical direction when capturing the head in two dimensional. The improvement in the rate of success of moving the mouse cursor in the vertical direction is 58%.

5.3 Ignoring tiny variations captured while holding the head stable

The web camera captures the slight movement of the user's head even though the user remains his head stable. The system ignores the slight movement by fixing the minimum threshold when the user remains his head stable. The system is tested before and after applying fuzzy logic with 10 users by asking them to face the web camera by holding their heads stable without moving.



(a)



(b)

Figure 7: Cursor movement when the head remains stable (a) before and (b) after applying 3D head capturing and fuzzy logic.

Fig. 7(a) shows the result before applying the 3D head capture and fuzzy logic where the system captures the slight movement of the head even though the user remains his head stable and the same is reflected in the cursor

movement in the computer window screen. Whereas, the Fig. 7(b) shows the result after applying the 3D head capture and fuzzy logic where the system ignores the slight movement of the head captured by the web camera when the user remains his head stable; the mouse cursor movement retains the position with no change in the screen.

6 Addressing feature loss

Unintentional head moves of the users often lead the current system to lose the tracking of facial features. The system ignores the sudden unintentional head movement of the user such as turning back and bending the head to pick something, by fixing the maximum threshold. The system is tested before and after applying fuzzy logic with 10 users by asking them to move the head to and fro all four directions as shown in Fig. 8 within 5 seconds. The user has to move the head fast to complete this task within 5 seconds.

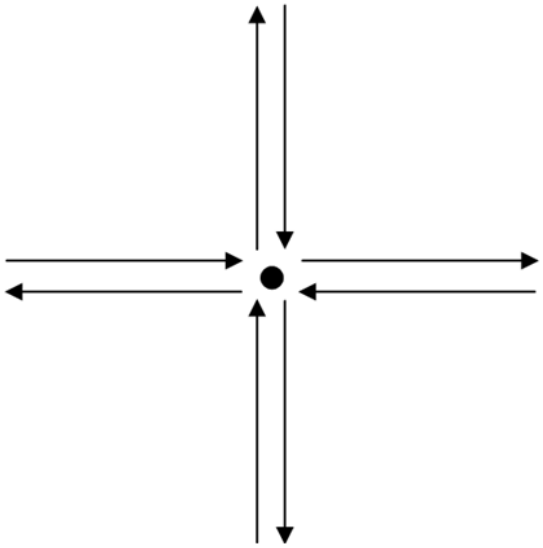
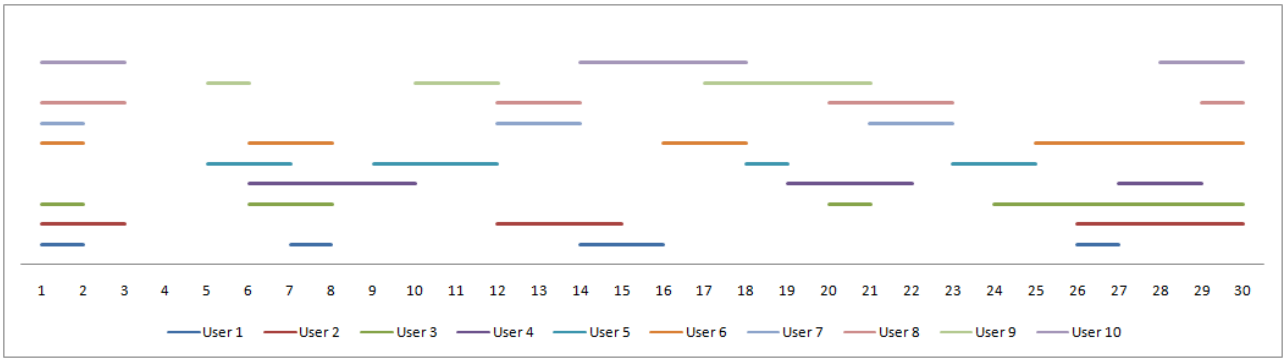
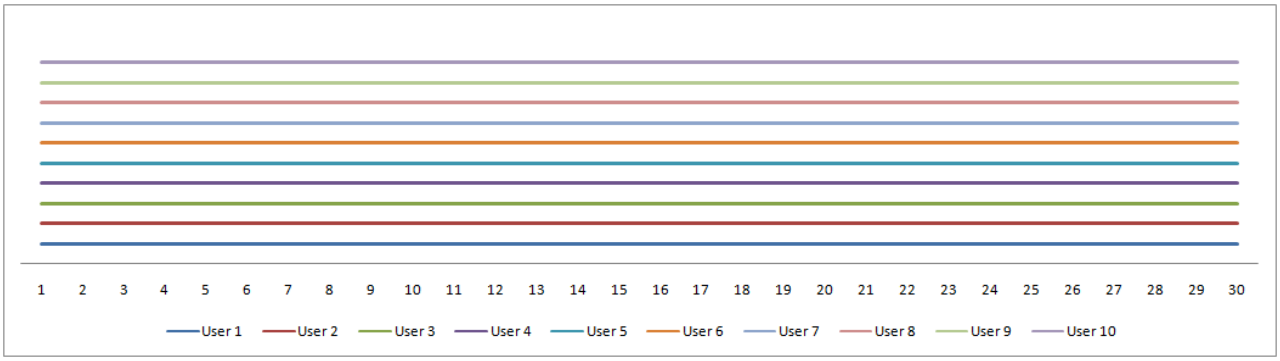


Figure 8: The direction of the head movement to test feature loss.



(a)



(b)

Figure 9: Result of testing feature loss (a) before and (b) after applying 3D head capturing and fuzzy logic.

The success rate of attainment of avoiding feature loss is 37.7% as shown in Fig. 9(a) which shows the result before applying the 3D head capture and fuzzy logic where the system often fails to capture the head of the user moves fast or the head moves out of the window frame. The lines in the figure show the capturing of the head by the camera while the blank area denotes the missing head in the respective frames shown on the horizontal axis.

The success rate of attainment of avoiding feature loss after applying the 3D head capture and fuzzy logic is 100% as shown in Fig. 9(b) where the system ignores the sudden unintentional movement of the head. The rate of the head movement captured by the web camera during the

sudden unintentional movement of the user falls beyond the maximum threshold. The system retains the mouse cursor position on the screen ignoring the sudden unintentional movement of the head; hence no feature loss.

The success rate of tracking the facial feature in various researches is compared and shown in Table 8.

Table 8: Comparison of the success rate of tracking the facial feature

Kim et al. [69]		Silwal et al. [70]	Wang et al. [71]	Rahib et al. [72]		Proposed Fuzzy-3D Method
Slow films	Fast videos			Head	Eye blink	
97.98%	91.58%	94.37%	>90%	98.12%	93.48%	100%

Kim et al. [69] used KLT and SegNet landmark detectors to obtain 97.98 % for slow films and 91.58 %for fast videos in tracking face landmarks. Silwal et al. [70] used a Convolutional Neural Network with a Softmax classifier to improve the accuracy of facial recognition by 94.37 %. When the moving speed is no more than 20 pixels per action, Wang et al. [71] found that the accuracy of controlling the mouse cursor is greater than 90 %. For the head and eye blink classifications, Rahib et al. [72] attained accuracies of 98.12 %and 93.48 %, respectively.

7 Conclusion

The advantage of mouse GUI operations for people with movement disabilities is the main topic of this article. The use of web cameras is recommended as an alternative to expensive head-mounted devices and expensive hardware systems. The head movement is a biological phenomenon of fuzziness, thus the system used fuzzy logic in its decision-making to identify the distance, direction, and rate of head movement. This increased the efficiency of operating the mouse. The suitable criteria were established to reject both predicted and unexpected head motions. To use the standard GUI interactive capabilities, the mouse pointer must be able to travel both horizontally and vertically.

This research has focused on enhancing the efficiency of controlling the mouse cursor in the hands-free computing system. Though the web camera captures the sequence of images in two-dimensional, the proposed system calculates the users' head movement in three-dimensional to achieve the horizontal and vertical movement of the cursor. To avoid the loss of facial features, the unintentional head movements are ignored and the movement of the mouse cursor is mapped only with the intentional movements of the head by applying fuzzy logic. The results of achieving the horizontal and vertical movement of the cursor are significant when compared with the existing system. The system successfully ignores the slight movement of the head captured by the web camera when the user remains the head stable, and the feature loss is completely avoided. However, the system can be improved in terms of accuracy and speed by detecting the face by using deep learning-based approaches.

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A Machine Learning Based Framework For Bankruptcy Prediction In Corporate Finances Using Explainable AI Techniques

Tabassum Maktum[1], Namita Pulgam[2], Vaishnavi Chandgadkar[3], Prachi Pathak[3] and Aditya Solanki[3]
[1]Department of Computer Engineering, School of Engineering & Technology, Anjuman I Islam's Kalsekar Technical Campus, New Panvel, Maharashtra, India.
[2]Department of Computer Science and Engineering (Data Science), D J Sanghvi College of Engineering, Mumbai, Maharashtra, India
[3]Department of Computer Engineering, Ramrao Adik Institute of Technology, D Y Patil Deemed to be University, Navi Mumbai, Maharashtra, India.
tabassum.maktum@aiktc.ac.in, Namita.Pulgam@djsce.ac.in, chandgadkar.vaishnavi@gmail.com, prachii1006@gmail.com, adityasolanki303@gmail.com,

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Forecasting bankruptcy within corporate finances is an indispensable endeavor crucial for sustaining business growth and fostering stability. The paper presents a methodology to redefine the conventional approach to bankruptcy prediction within corporate finance. Through the adept utilization of advanced machine learning techniques, notably classification models, a dynamic and adaptable framework is established, enabling the systematic categorization of companies based on their bankruptcy risk profiles. Moreover, the methodology addresses the inherent challenge of data bias by integrating oversampling techniques like the Synthetic Minority Over-sampling Technique (SMOTE), thereby ensuring a more equitable representation of minority class samples and bolstering the model's predictive accuracy. The resulting model delivers timely and precise forecasts of bankruptcy risk, fortified by crucial recommendations such as the Altman Z-Score for vulnerability assessment, Debt-to-Equity Ratio for insights into leverage, Quick Ratio for assessing liquidity, and Explainable AI Techniques like SHapley Additive exPlanations (SHAP) analysis for transparent interpretations. This comprehensive approach equips stakeholders with tailored recommendations, empowering them to proactively safeguard their organizations' financial well-being and avert the perils of bankruptcy. The comparative analysis presented in paper demonstrates that the proposed method assesses the bankruptcy risk more accurately. The integration of Explainable AI techniques and key financial metrics helps the stakeholders to take vital decisions about corporate finances.

Povzetek: Opisano je napovedovanje stečaja v podjetniških financah z uporabo tehnik razložljive umetne inteligence. Z uporabo naprednih tehnik strojnega učenja, kot so klasifikacijski modeli in tehnike prekomernega vzorčenja (SMOTE), avtorji razvijejo dinamičen okvir za kategorizacijo podjetij glede na tveganje stečaja. Vključitev meritev, kot so Altmanov Z-izid, razmerje med dolgom in kapitalom ter hitro razmerje, skupaj z analizo SHAP, zagotavlja pregledne interpretacije in praktične vpoglede za zainteresirane strani.

1 Introduction

In the intricate landscape of corporate finance, the looming specter of bankruptcy poses a significant challenge, demanding agile manoeuvring to shield stakeholders' interests and ensure the sustained vitality of the organization. When a company teeters on the brink of insolvency, its reverberations are profound, affecting every facet of its operations, financial stability, and brand reputation. Bankruptcy, a stark manifestation of financial distress, not only inflicts substantial losses upon investors but also serves as a stark indicator of underlying operational inefficiencies, strategic miscalculations, or external economic pressures. In today's volatile and dynamic global marketplace, the proactive anticipation and adept management of bankruptcy risk have become imperative for modern enterprises striving for longevity and competitiveness. Amidst the prevailing uncertainties and cut-throat competition, the ability to anticipate and pre-emptively mitigate the threat of bankruptcy emerges as a pivotal strategic priority. Acknowledging the nuanced nature of financial distress, companies must employ robust analytical frameworks, sophisticated risk assessment methodologies, and well-orchestrated contingency plans to effectively identify vulnerabilities and fortify their financial resilience. By integrating bankruptcy anticipation as a cornerstone of their strategic approach, businesses not only fortify their resilience against unforeseen economic downturns but also

foster sustainability and engender long-term value creation. This proactive stance not only shields against potential crises but also lays the groundwork for enduring success in an ever-evolving, interconnected global economy, positioning organizations to navigate turbulent waters with confidence and agility.

Traditional systems for bankruptcy prediction often lack explainability regarding how financial indicators contribute to predictions and remain static, failing to adapt to changing economic conditions. Moreover, they may suffer from imbalanced datasets, biased towards nonbankrupt instances, and rely on linear assumptions, potentially overlooking nonlinear patterns. This imbalance in the dataset, favouring non-bankrupt instances, may lead to an underestimation of bankruptcy risks. Therefore, there is a pressing demand for an innovative approach capable of accurately forecasting bankruptcy in corporate finances, empowering stakeholders with timely insights to proactively safeguard their organizations' financial stability. Recognizing the pivotal role of timely recognition of financial distress in ensuring sustained business growth and solidity, the proposed methodology aims to redefine bankruptcy prediction in corporate finance, ushering in an era of proactive risk management. Hence, proposed methodology sets a new standard for bankruptcy prediction, empowering businesses to navigate the complexities of the modern economic landscape with agility and confidence. Below objectives outline the key components of the proposed methodology aimed at addressing the challenges of bankruptcy prediction within corporate finance:

- Develop a predictive analytics framework for timely insights into financial vulnerabilities, ensuring stability.
- Implement a model using the Altman Z Score to assess financial health and bankruptcy risk.
- Use the Debt Equity Ratio to evaluate financial leverage and bankruptcy risk.
- Employ the Quick Ratio to gauge liquidity and signal potential short-term distress.
- Analyze SHAP values to interpret predictions, identify key bankruptcy factors, and offer actionable insights to mitigate risks.

The paper underscores the critical importance of forecasting bankruptcy in corporate finances, highlighting the need for early identification of financial instability and proactive risk mitigation. It reviews traditional and modern bankruptcy prediction methods, including machine learning and oversampling techniques to handle data bias. The proposed methodology focuses on advanced machine learning techniques and oversampling. Results are presented and evaluated, followed by a summary of key findings, implications for stakeholders, limitations, and suggestions for future research.

2 Related work

Evident research done in [1] showcases the efficacy of the Kmeans-SMOTE Integration method in addressing the challenge of imbalanced data within the context of classifying financial distress companies. This study yielded notable results. Support Vector Machine (SVM) achieved an impressive accuracy rate of 99.1%, while Na¨ıve Bayes demonstrated a respectable accuracy of 87%. The success of these models was attributed to the utilization of the Kmeans-SMOTE method, which effectively mitigated data imbalance. This approach not only enhanced classification accuracy but also underscored its potential to bolster the reliability of financial distress prediction systems.

Research in [2] demonstrated the effectiveness of machine learning and data balancing techniques for bankruptcy prediction. Bagging achieved 90.75% accuracy, with Random Forest (RF) at 91.61%. Support Vector Machine Linear (SVML) and Radial (SVMR) reached 80.06% and 79.96%, respectively, while Artificial Neural Network (ANN) and Decision Tree (DT) achieved 81.92% and 81.43%. The study utilized five data balancing methods—random oversampling, SMOTE, ADASYN, random undersampling, and near miss—highlighting the importance of these techniques in enhancing model accuracy and robustness.

Research conducted in [3] addresses the significant risk of bankruptcy among start-up companies through the utilization of advanced artificial intelligence techniques for predictive analysis. The study employs a range of algorithms, including CatBoost, RandomForest, XGBoost, AdaBoost, MLP, LogReg, and SVM, to categorize key features into critical credit aspects—such as Capacity, Capital, Collateral, Conditions, and Character—alongside the incorporation of Shapley values. This approach provides insights into factors predicting bankruptcy and enhances transparency with a "glass-box" model. CatBoost achieved notable accuracy with a precision of 87%.

In [4], the study introduces a cutting-edge ensemble learning framework addressing corporate financial distress risks within the knowledge economy. Leveraging explainable artificial intelligence (XAI) techniques such as SHAP explanations and ICE interpretations, the research enhances transparency and accuracy in financial distress prediction. Empirical experiments using Polish company data reveal the GBoost model with random oversampling (ROS) as the top performer, offering insights into key indicators of distress through local PDP interpretations and actionable strategies for improvement via ICE interpretations. The study's global interpretation with SHAP's feature importance and interaction results aligns with financial experts' insights, emphasizing knowledge-driven innovation.

In [5], the study analyzes 5 banking companies' financial health with a modified Altman Zscore, examining key indicators like Working Capital to Total Assets (X1), Retained Earnings to Total Assets (X2), Earnings Before Interest Taxes to Total Assets (X3), and Market Value of Equity to

Book Value of Liabilities (X4). Findings indicate one company, Bank Mega tbk (MEGA), faces bankruptcy risk with an average Z-score of -3.32, while Bank Negara Indonesia (persero) tbk (BBNI), Bank Bukopin tbk (BBKP), Bank Mandiri (persero) tbk (BMRI), and Bank Rakyat Indonesia tbk (BBRI) demonstrate stability with Z-scores ranging from 4.38 to 4.62. This highlights the method's effectiveness in predicting corporate bankruptcy.

In [6], the research delves into the implementation of India's Insolvency and Bankruptcy Code 2016, aimed at modernizing the country's corporate insolvency regulations. Focusing on the Altman-Z score model, the study forecasts the safety levels of Indian banks regarding potential insolvency and bankruptcy. Results categorize banks into 'Safe,' 'Gray,' and 'Distress' zones based on Z-score thresholds, highlighting the robustness of Indian banks during the study period. Notable variations in bank performance were observed in the latter years, emphasizing the need for proactive management to mitigate insolvency risks.

In [7], the research assesses the performance of various machine learning models in predicting financial distress among listed companies in Vietnam. The study reveals that the extreme gradient boosting model achieved the highest accuracy of 95.66%, followed by the artificial neural network (ANN) with 91.68 accuracy. Through the application of SHAP values, the research identifies key financial indicators—such as long-term debts to equity, enterprise value to revenues, accounts payable to equity, and diluted EPS—that significantly influence distress predictions. The findings not only offer insights into the interpretability of black-box machine learning models but also provide credit rating companies with a new method to predict bond issuer default possibilities.

In [8], the research focuses on creating an ensemble model for predicting financial distress in companies within the Visegrad Group (V4) region. Utilizing real data from over 550,000 companies in Central Europe from the Amadeus database, the study trains and validates the model using 27 financial variables from 2016 to predict financial distress in 2017. The model identifies five significant predictors: current ratio, return on equity, return on assets, debt ratio, and net working capital. The hybrid model, combining RobustBoost, CART, and k-NN algorithms, achieves a superior accuracy of 94.25%, outperforming individual methods and offering a novel, high-performance tool for estimating financial distress risks in the V4 region.

In [9], the research focuses on developing a model to estimate the probability of corporate bankruptcy using various machine learning models. The study addresses the challenges of imbalanced data by employing data balancing techniques such as random undersampling and Synthetic Minority Over Sampling Technique (SMOTE). Using data from 2009 to 2013 on Poland manufacturing corporates and 64 selected financial indicators, the models—support vector machine (SVM), J48 decision tree, Logistic Model Tree (LMT), Random Forest (RF), and Decision Forest—are trained to predict bankruptcy occurrences. Results indicate significant improvement in predictive accuracy with machine learning techniques, particularly with SMOTE balancing. The Decision Forest model stands out with an impressive accuracy of 99%, followed by Random Forest at 98.7%, LMT at 93.8%, J48 decision tree at 92.3%, and SVM at 92%.

The work in[10] represents the analysis of financial risks associated with small and medium-sized businesses. The authors have utilized the Neural network method for the prediction and the proposed method is accurate in terms of prediction. The combined and compromise solution based approach for analysing financial risks for large businesses is presented in [11]. The proposed method follows the multiple attributes based decision and utilizes intuitionistic fuzzy sets. The paper [12], presents a neural network based method to analyse the financial fraud. Here, also neural network and Principal Component Analysis methods are employed. The paper presents the utilization of machine learning algorithms for financial analysis. Few more related work is presented in [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24],[25], [26]. The comparative analysis of some of the existing works is presented in Table 1.

The following are the research gaps identified after examining the recent relevant works.

- The some of the existing models lack clarity in explaining how financial indicators contribute to bankruptcy predictions, which limits its explainability.
- Due to the static nature, the majority of the models fail to adapt to changing economic conditions, which may result in decreased accuracy over time.
- An imbalanced dataset, with a bias towards the majority class (non-bankrupt instances), may lead to an underestimation of bankruptcy risks.
- The model's linear assumptions result in it assuming linear relationships between financial indicators and bankruptcy, potentially overlooking nonlinear patterns.
- By focusing solely on internal metrics, most of the models neglects external factors that could impact bankruptcy risk, contributing to its limited scope.

3 Proposed work

This study explores the critical domain of bankruptcy prediction in corporate finance, with the objective of enabling proactive financial management and strengthening business resilience amidst evolving challenges.

A visual representation of the sequential processes inherited in the proposed system is provided in Figure 1, offering a clear overview of its methodology and essential

Table 1: Comparative analysis of related work

Study	Methodology	Performance	Key Observations
[1]	Uses Kmeans-SMOTE method to mitigate data imbalance	SVM 99.1%, Naive Bayes 87%	enhance classification accuracy and mitigate data imbalance challenge
[2]	Applied five data balancing methods (random oversampling, SMOTE, ADASYN, Random undersam pling, and near miss)	Bagging 90.75%, SVML 80.06%, SVMR 79.96%, ANN 81.92%, RF 91.61%, Boosting 78.02%, KNN 59.72%, DT 81.43%, Logistic 65.60%	Represents significance of advanced machine learning techniques and proper data balancing
[3]	Top features are categorized into credit aspects (Capacity, Capital, Collateral, Conditions, Character), combined with Shapley values.	CatBoost (87%), RandomForest (83%), XGBoost (86%), AdaBoost (86%), MLP (65%), LogReg (59%), SVM (46%)	Design of the glass-box model enhances transparency
[4]	Local PDP and ICE methods were used for analysis	SHAP explanations for key indicators, ICE interpretations for improvement strategies	SHAP's results aligns with financial experts' insights
[5]	Z-score analysis for corporate bankruptcy prediction	Identified one unhealthy and four stable companies using a modified Altman Z-score	proposed model is more effective in predicting corporate bankruptcy
[6]	Altman-Z score model for Indian bank insolvency forecast	$Z > 2.99$ = "Safe," $1.81 < Z < 2.99$ = "Gray," $Z < 1.81$ = "Distress" zones	Emphasize on at modernizing the country's corporate insolvency regulations
[7]	Use various ML models for distress prediction	XGBoost (95.66%), Random Forest (85.35%), LogReg (86.23%), ANN (91.68%), DT (82.80%), SVM (87.89%)	Research findings offer insights into the interpretability of black-box machine learning models
[8]	Apply Ensemble methods for distress prediction in the regional context	RobustBoost (94.25%), CART (92.11%), k-NN (91.65%), Voting (92.69%), Avg Model (92.80%), Final Model (94.25%)	Ensemble approach presents a novel technique by offering an interpretability and high-performance
[9]	Apply ML models and also employ data balancing techniques	Decision Forest (99%), SVM (92%), J48 DT (92.3%), LMT (93.8%), RF (98.7%)	Significant improvement in predictive accuracy with ML techniques, and SMOTE balancing
[13]	Enhanced NN training for improved bankruptcy predictions	PSO (52.89%), MOA (72.24%), PSO-MOA (99.73%)	Hybrid approach enhances the speed of prediction and ensures higher accuracy
[14]	SAE technique for bankrupt firm prediction accuracy	SAE + Softmax Classifier achieves 87.9% accuracy for the Darden dataset and 98% accuracy for the Polish dataset	Better performance than traditional machine learning algorithms

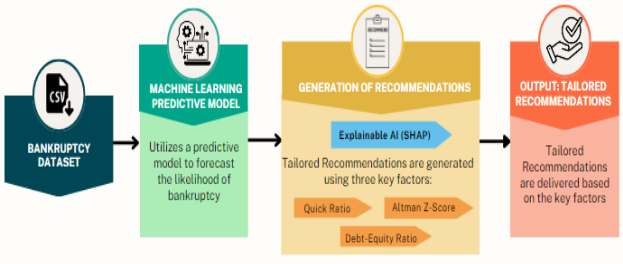


Figure 1: Architecture of proposed work

components. The architecture begins with the Machine Learning Predictive Model employs a robust framework for bankruptcy prediction by leveraging the US Company Bankruptcy Prediction Dataset. Initially, data imbalance is addressed through SMOTE oversampling, followed by data exploration, preprocessing, and normalization. This sets the stage for implementing six machine learning models, providing stakeholders with powerful tools for financial risk assessment. Based on the model's insights, tailored recommendations are generated to mitigate financial risks, focusing on the Altman Z-Score, Quick Ratio, and Debt-to-Equity Ratio, along with SHAP values for explainability. These recommendations guide companies in proactively managing bankruptcy risks and maintaining financial stability.

In this study, the main objective is to assess and compare

the performance of multiple classifiers on imbalanced and balanced datasets using their default configurations. We aimed to establish a baseline performance for each model without introducing additional tuning complexity, thereby focusing our analysis on the impacts of class balancing via SMOTE rather than on optimized model settings. The US Company Bankruptcy Prediction Dataset [27], used in this study spans from 1999 to 2018 and includes financial data for 78,682 records of mid- and large-cap companies listed on the NYSE and NASDAQ. The dataset contains 18 financial indicators covering profitability, liquidity, and leverage, labeled as ”alive” or ”failed” to indicate solvency status. Companies come from diverse sectors, including technology, manufacturing, healthcare, finance, and consumer goods, making the dataset broadly representative and enhancing the model's generalizability across industries and economic conditions.

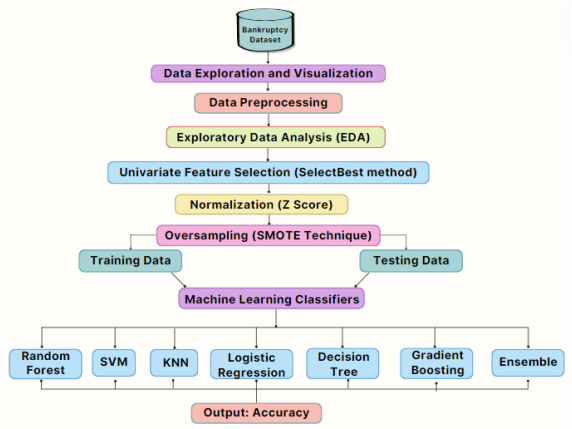


Figure 2: Workflow of bankruptcy prediction model

Illustrating the intricate process involved in building a dependable bankruptcy prediction model, Figure 2 emphasizes the essential steps critical for ensuring the model's accuracy and reliability. It starts with data exploration and pre-processing phase that involves thorough examination and visual representation of the dataset. Essential preprocessing steps ensured data integrity by checking for missing values, summarizing numerical features, and encoding the target variable. Exploratory Data Analysis (EDA) followed, using a correlation matrix and heatmap to identify key feature relationships. Feature selection with SelectKBest highlighted the most relevant features, enhancing model performance. The dataset was then normalized with StandardScaler and balanced using SMOTE to address class imbalance. The resampled data was split into training (80%) and testing (20%) sets. Various classification algorithms, including Random Forest, Decision Tree, Logistic Regression, Gradient Boosting, SVM, KNN, and an Ensemble model, were trained and evaluated on these sets, with performance metrics calculated to compare their effectiveness.

Algorithm 1 outlines the steps required to clean and prepare the dataset, including handling missing values, encoding categorical variables, and normalizing the data o ensure the quality and integrity of the input data for model training. In the referred dataset, the only categorical feature is the target variable *status_label*, which has two possible values: ”alive” and ”failed.” We used binary encoding to represent these categories, mapping ”alive” to 1 and ”failed” to 0. Since this target variable is binary, it does not have high cardinality (a large number of unique categories). Therefore, high cardinality handling methods like target encoding, frequency encoding, or clustering categories are unnecessary for this dataset. Our simple binary encoding is both efficient and sufficient for this feature.

Algorithm 1 Data Preprocessing

Input: US Company Bankruptcy Prediction Dataset (78,682 rows, 19 attributes)
Output: Preprocessed Data
Start
Step 1: Load the Dataset D.
Step 2: Handle Missing Values
- For numerical values x_{ij} in feature j:
  - $x_{ij} = \begin{cases} \bar{x}_j & \text{if } x_{ij} \text{ is missing} \\ x_{ij} & \text{otherwise} \end{cases}$
- For categorical values x_{ij}:
  - $x_{ij} = \text{mode}(x_{\cdot j})$

Step 3: Encode Categorical Variables
- Convert categorical attributes to numerical values using one-hot encoding:
  - $x_{ij}(k) = \begin{cases} 1 & \text{if category } k \text{ matches} \\ 0 & \text{otherwise} \end{cases}$

Step 4: Adjust Column Names
- Rename columns for clarity and consistency.

Step 5: Conduct Exploratory Data Analysis (EDA)
- Visualize the distribution of the target variable.
- Summarize numerical features: compute mean $\bar{x}_j$, median $\tilde{x}_j$, and standard deviation σ_j for each numerical feature j.

Step 6: Encode Target Variable
- Convert 'status label' to numerical values:
  - $y_i = \begin{cases} 1 & \text{if 'alive'} \\ 0 & \text{if 'failed'} \end{cases}$

Step 7: Feature Selection
- Apply SelectKBest method with chi-square statistics: Select top k features based on chi-square test with target y.

Step 8: Normalize Data
- Scale features to zero mean and unit variance:
  - $x_{ij} = \frac{x_{ij} - \bar{x}_j}{\sigma_j}$

End

Algorithm 2 outlines the method for addressing class imbalance in the dataset by generating synthetic samples for the minority class using techniques such as Synthetic Minority Over-sampling Technique (SMOTE). This approach helps to enhance the model's performance by ensuring that the classifier does not become biased towards the majority class, thereby improving its ability to correctly predict bankruptcy cases. The algorithm begins by identifying the minority class samples, then creates synthetic samples by interpolating between existing minority samples. This process increases the representation of the minority class, leading to a more balanced dataset and, consequently, a more reliable predictive model. The proposed method selects the optimal number of nearest neighbors (k) by experimenting with various values and evaluating the impact on the performance of the model. It has been observed that k=5 provided the best balance between enhancing the minority class representation and maintaining

model stability. Also, utilization of five neighbors yielded a more representative oversampling effect without introducing noise. Algorithm 3 covers the training of various

Algorithm 2 SMOTE Oversampling

Input: Preprocessed Data (with imbalanced classes)
Output: Balanced Data (after SMOTE oversampling)
Start
Step 1: Begin the SMOTE oversampling process
Step 2: Apply SMOTE (Synthetic Minority Over-sampling Technique)

- Set the sampling strategy parameter to 0.5.
- Generate synthetic samples for the minority class to balance the class distribution.

Step 3: Generate synthetic samples

- For each minority class example x_i:
  - Calculate the k nearest neighbors (using Euclidean distance or other distance metrics).
  - Randomly select one of the k nearest neighbors x_{zi}.
  - Generate a synthetic example x_{new} using the formula:

$$x_{\text{new}} = x_i + \lambda \times (x_{zi} - x_i)$$

where λ is a random number between 0 and 1.

Step 4: Repeat steps 1-3 until the desired balance between minority and majority classes is achieved
End

classification algorithms, including Random Forest, Decision Tree, Logistic Regression, Gradient Boosting, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and an ensemble model. Their performance is evaluated using a range of metrics such as accuracy, precision, recall and F1 score. These metrics provide a comprehensive view of each model's ability to correctly predict bankruptcy cases while minimizing false positives and false negatives. The performance metrics of all models are then compared, and the best-performing model is selected based on its ability to balance accuracy, interpretability, and computational efficiency.

For the ensemble model, weighted voting approach is implemented that assigns weights based on individual model performance on testing data. This approach balanced model contributions, prioritizing models with higher accuracy. The models are selected based on their performance in preliminary testing and their complementary strengths in handling various data characteristics.

Algorithm 4 provides a comprehensive framework for analyzing financial metrics and generating tailored recommendations to mitigate bankruptcy risks. The process begins by utilizing the best-performing predictive model from previous algorithms to identify companies at risk of bankruptcy. This model leverages key financial indicators such as the Altman Z Score, Debt Equity Ratio, and Quick Ratio to assess the financial health of companies. In addition to generating recommendations, the algorithm employs SHAP (SHapley Additive exPlanations) analysis to provide model interpretability.

4 Results and discussions

The major objective of the proposed method is to predict corporate bankruptcy by applying multiple machine learning classifiers on both imbalanced and balanced datasets. The tested algorithms included Random Forest, Decision Tree, Logistic Regression, Gradient Boosting, Support

Algorithm 3 Classification Model Training

Input:
X: Feature matrix after preprocessing and SMOTE oversampling
y: Target variable vector after preprocessing and SMOTE oversampling
Output: Trained Models and Performance Metrics
Start
Step 1: Train Classification Algorithms
for each classification algorithm Alg_i (where $i = 1, 2, \ldots, N$) **do**
Initialize Algorithm Alg_i
Train Algorithm Alg_i on X_{train}, y_{train}
Random Forest:

- $y^{\text{RF}} = \text{RF}(X, \text{parameters})$

Decision Tree:

- $y^{\text{DT}} = \text{DT}(X, \text{parameters})$

Logistic Regression:

- $y^{\text{LogReg}} = \text{LogReg}(X, \text{parameters})$

Gradient Boosting:

- $y^{\text{GB}} = \text{GB}(X, \text{parameters})$

Support Vector Machine (SVM):

- $y^{\text{SVM}} = \text{SVM}(X, \text{parameters})$

K-Nearest Neighbors (KNN):

- $y^{\text{KNN}} = \text{KNN}(X, \text{parameters})$

Ensemble Model (Simple Voting):

- $y^{\text{Ensemble}} = \text{Ensemble}(X, \text{parameters})$

end for
Step 2: Predict on Testing Set
for each trained algorithm Alg_i **do**
$y^{\text{test},i} = Alg_i(X_{\text{test}})$
end for
Step 3: Evaluate Performance Metrics

- Calculate performance metrics Metrics_i such as Accuracy, Precision, Recall, and F1-Score using $y^{\text{test},i}$ and y_{test}:
- **Accuracy:**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision:**

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall (Sensitivity):**

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **F1-Score:**

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Step 4: Select Best Model

- Compare the performance metrics Metrics_i for all algorithms and select the best-performing model.

End

Vector Machine, K-Nearest Neighbors, and an Ensemble model. First, the model's performance is tested on the imbalanced dataset to understand the effects of class imbalance on accuracy, precision, recall, and F1-score. Then, the SMOTE was applied to address class imbalance by oversampling the minority class. The training process is repeated on this newly balanced dataset and comparative analysis of different classifiers, before and after applying SMOTE is performed. In the later phase, SHAP analysis id performed to generate tailored recommendations to mitigate corporate finance risks.

4.1 Experimental setup

The proposed method utilizes the bankruptcy distribution within the US Company Bankruptcy Prediction Dataset [27]. This dataset encompasses two target labels: "alive" for companies without bankruptcy history and "failed" for those that have undergone bankruptcy. Initially, the dataset comprised 73,462 instances labelled as "alive" and 5,220 instances labelled as "failed." To address dataset

imbalance, SMOTE oversampling was employed, increasing ”failed” instances to 36,731 and achieving a balanced dataset with 110,193 entries.

We have used an 80-20 train-test split of the dataset, with 80% of the data allocated for model training and 20% for testing. This split was applied uniformly across all machine learning models in our study. The focus is given on training and testing models using the single train-test split. This allowed us to analyze classifier performance on a stable partition of data while keeping the experimental process straightforward.

4.2 Experimental analysis

Illustrated in Figure 3 is the comparison of the target variable distribution before and after applying the SMOTE technique, highlighting the effective rebalancing achieved. This is crucial for ensuring robust performance and reliability in the bankruptcy prediction model. We did not observe signs of overfitting in our models. The performance metrics, such as accuracy, precision, recall, and F1-score, remained consistent across both training and test datasets, for each model. Given that our primary objective was a comparative analysis on imbalanced vs. balanced datasets, we relied on performance stability across the 80-20 train-test split to gauge generalization rather than implementing additional overfitting mitigation strategies.

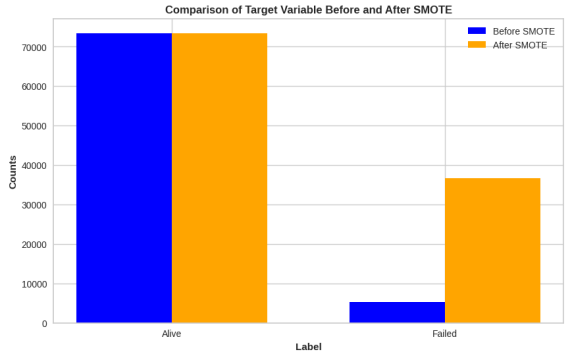


Figure 3: Before vs after SMOTE - target variable comparison

Table 2 summarizes the performance metrics (accuracy, precision, recall, F1-score) of various machine learning algorithms before applying SMOTE.

Table 2: Evaluation metrics of various models (before SMOTE)

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	93.61	93.63	99.95	96.69
Decision Tree	89.74	94.66	94.31	94.48
Logistic Regression	93.21	93.23	99.97	96.48
Gradient Boosting	93.29	93.35	99.93	96.52
SVM	93.23	93.23	100.00	96.49
KNN	93.12	93.62	99.40	96.42
Ensemble	93.35	93.36	99.98	96.56

The performance evaluation graph in Figure 4 illustrates pre-SMOTE results, highlighting insights into machine learning classifier effectiveness on an imbalanced dataset. While all models show high accuracy and recall for the majority class (”alive”), precision varies notably. Models like Random Forest and Gradient Boosting exhibit superior precision compared to Logistic Regression and SVM, highlighting challenges in predicting the minority class (”failed”). Despite generally high F1-scores, indicating a balance between precision and recall, the findings underscore the need to tackle data imbalance.

Algorithm 4 Generation of Recommendations

Input:
Best Performing Model (from Algorithm 3)
Financial Metrics Analysis (including Altman Z-Score, Quick Ratio, Debt-to-Equity Ratio)
Output: Tailored Recommendations for Mitigating Bankruptcy Risks
Start
Step 1: Begin the process of generating recommendations
Step 2: Identify At-Risk Companies

- Utilize the best performing classification model (from Algorithm 3) to predict bankruptcy risk for companies.

Step 3: Analyze Financial Metrics

- **Altman Z-Score Calculation:**

$$Z = 1.2 \times X_1 + 1.4 \times X_2 + 3.3 \times X_3 + 0.6 \times X_4 + 1.0 \times X_5$$

where:

  - X_1: Working Capital / Total Assets
  - X_2: Retained Earnings / Total Assets
  - X_3: Earnings Before Interest and Taxes (EBIT) / Total Assets
  - X_4: Market Value of Equity / Book Value of Total Debt
  - X_5: Sales / Total Assets

- **Quick Ratio:**

$$\text{Quick Ratio} = \frac{\text{Current Assets} - \text{Inventory}}{\text{Current Liabilities}}$$

- **Debt-to-Equity Ratio:**

$$\text{Debt-to-Equity Ratio} = \frac{\text{Total Debt}}{\text{Total Equity}}$$

Step 4: Explain Model Decisions

- Employ Explainable AI techniques (e.g., SHAP values) to interpret model predictions and feature contributions.

Step 5: Generate Tailored Recommendations

- Based on the analysis:
  - Recommend strategies to improve financial health, such as reducing debt levels:

$$\text{Reduce Debt} = \text{Current Debt} - \text{Target Debt}$$

  - Suggest operational adjustments to enhance profitability and sustainability.

Step 6: Deliver Recommendations

- Present actionable insights and recommendations to stakeholders.

End

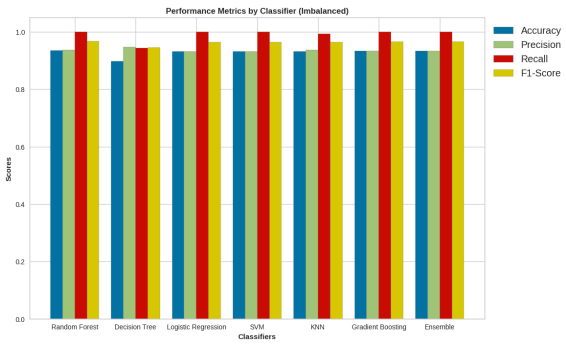


Figure 4: Evaluation metrics comparision (before SMOTE)

Table 3 displays the performance metrics of various models after applying SMOTE to balance the dataset.

Table 3: Evaluation metrics of various models (after SMOTE)

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	95.34	95.57	97.56	96.57
Decision Tree	86.74	91.52	88.37	89.92
Logistic Regression	67.41	67.48	98.99	80.25
Gradient Boosting	74.35	76.00	91.00	83.00
SVM	68.64	68.33	99.01	80.86
KNN	91.61	99.21	88.17	93.36
Ensemble	92.75	91.00	98.94	94.81

The performance evaluation graph in Figure 5 shows the results after applying the SMOTE technique and reveals several key insights into the effectiveness of various machine learning classifiers on a balanced dataset. Post-SMOTE, Random Forest emerges as the top performer across all metrics: accuracy, precision, recall, and F1-score. With an accuracy of 95.34%, precision of 95.57%, recall of 97.56%, and balanced F1-score of 96.57%, Random Forest proves its robustness and reliability. These results affirm its capability to accurately detect true positives (actual bankruptcies) while minimizing false positives, establishing it as the preferred model for predicting corporate bankruptcy.

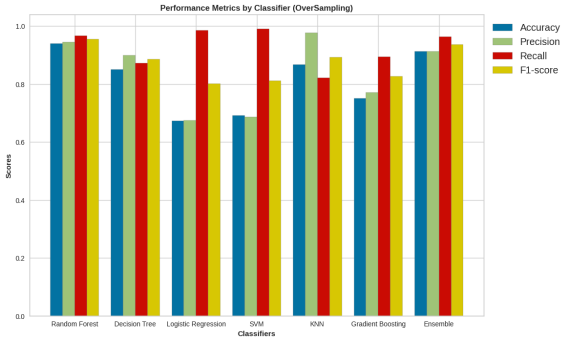


Figure 5: Evaluation metrics comparison (after SMOTE)

Utilizing Explainable AI (SHAP) as shown in Figure 6 enhanced model interpretability by detailing each feature's contribution to bankruptcy prediction, aiding stakeholders in comprehending factors influencing model decisions. The SHAP analysis identified key financial features like the Debt-to-Equity (D/E) Ratio, components of the Altman Z-Score (such as working capital and retained earnings), liquidity measures (e.g., current ratio), and profitability metrics (net income and gross profit) as consistently important predictors across models. These features align closely with established financial theories on bankruptcy, where high leverage, low liquidity, and declining profitability increase bankruptcy risk. By emphasizing these financially relevant features, the SHAP analysis bridges the model's predictions with traditional financial insights, enhancing interpretability and practical relevance for stakeholders.

Several key financial metrics in Table 4 were calculated to provide tailored recommendations for companies at risk of bankruptcy. The Quick Ratio assessed liquidity, the Debt-to-Equity Ratio evaluated financial leverage, and the Altman Z-Score gauged overall bankruptcy risk.

A thorough evaluation of SMOTE's impact on seven machine learning algorithms, is also performed. These analysis include, accuracy, precision, recall, and F1-score metrics across different test set proportions (ranging from 10% to 90%) and their corresponding metric values.

The analysis of the accuracy metric depicted in Figure 7 provides significant insight into how various machine learning algorithms perform when exposed to increasing proportions of testing data. Random Forest consistently exhibits high accuracy levels across all testing data proportions, emphasizing its stability and adaptability across diverse datasets.

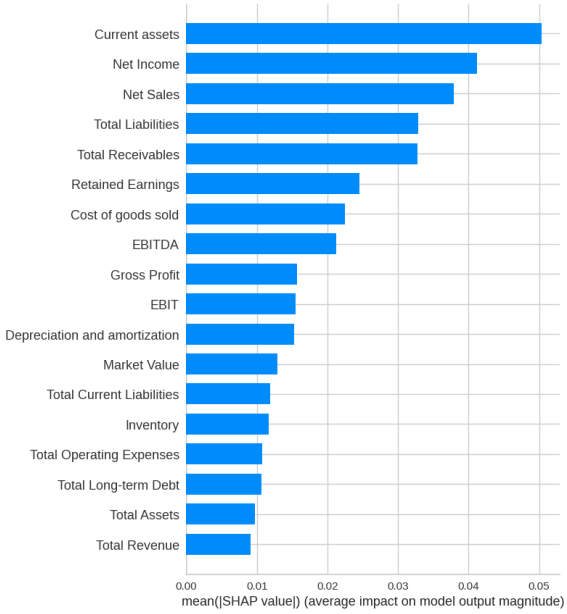


Figure 6: Explainable AI- SHAP analysis

Table 4: Recommendations for Financial Metrics

Metric	Recommendations
Quick Ratio	**Healthy -** High liquidity, low risk of short-term financial difficulties. **Acceptable -** Indicates moderate liquidity. **Cause for concern -** Low liquidity, potential difficulty in meeting short-term obligations.
Debt-to-Equity Ratio	**Conservative -** Indicates lower financial risk, less reliance on debt financing. **Moderate -** Balanced use of debt and equity financing. **Aggressive -** High financial risk, heavy reliance on debt financing.
Altman Z-Score	**Safe Zone** – Low Likelihood of Bankruptcy. **Grey Zone** – Moderate Risk of Bankruptcy. **Distress Zone** – High Likelihood of Bankruptcy.

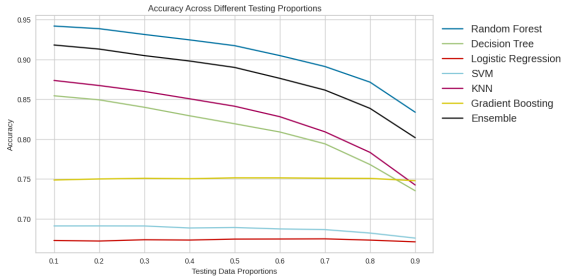


Figure 7: Accuracy of various classifiers

The analysis of the precision metric depicted in Figure 8 offers insights into machine learning algorithms' performance with increasing proportions of testing data. Initially, K-Nearest Neighbors (KNN) achieves the highest precision, followed by Random Forest and the Ensemble model. This trend underscores KNN's effectiveness in early identification of true positives. Random Forest and Ensemble models also maintain strong precision, highlighting their reliability across different testing data proportions.

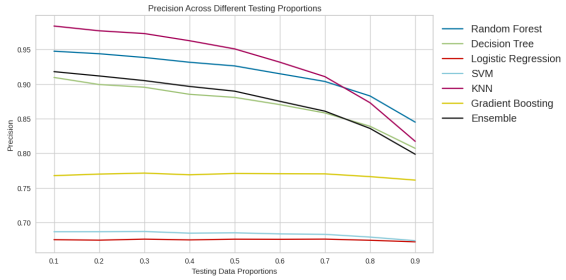


Figure 8: Precision of various classifiers

The analysis of the recall metric depicted in Figure 9 provides insights into machine learning algorithms' performance with increasing testing data proportions. Initially, Support Vector Machine (SVM) and Logistic Regression show notable increases in recall, indicating their effectiveness in identifying true positive instances. As testing data proportions increase, Ensemble and Random Forest models also demonstrate commendable rises in recall levels, particularly in the early testing phases, highlighting their reliability across diverse data splits. The Figure 10 illustrates how F1-scores evolve across different testing proportions, providing insights into each algorithm's performance under varying data splits. Random Forest and Ensemble models show significant increases in F1-scores initially, indicating their ability to balance precision and recall effectively. KNN and Decision Tree also exhibit notable rises in F1-scores during early testing phases, reflecting their capability to maintain balanced performance as the dataset size increases.

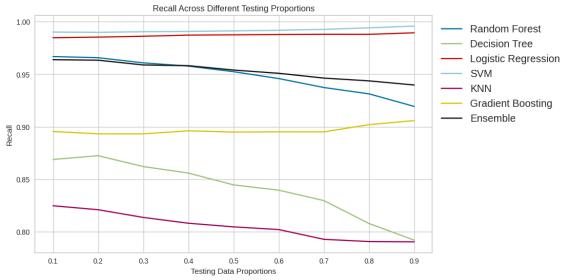


Figure 9: Recall of various classifiers

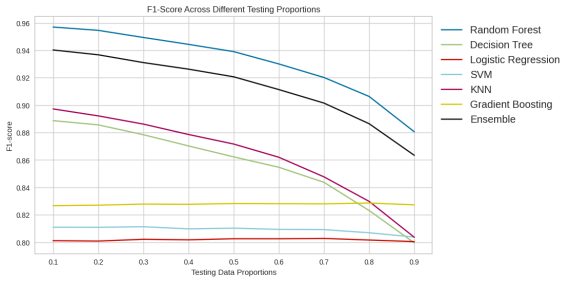


Figure 10: F1-Score of various classifiers

4.3 Performance analysis

This section elaborates the comparative analysis of proposed work and some of the existing works. Table 5 compares various research works and their incorporation of key methodologies. It highlights the comprehensive approach of the proposed work, which uniquely integrates all critical methodologies for effective bankruptcy prediction and provide tailored recommendations.

Table 5: Comparison of proposed work and existing research works

Author	Classification Model	SHAP	Altman Z score	SMOTE
[2]	✓	✗	✗	✓
[4]	✗	✓	✗	✗
[6]	✗	✗	✓	✗
[7]	✓	✓	✗	✗
[Proposed]	✓	✓	✓	✓

Accuracy measures the overall correctness of the model by calculating the proportion of true results (both true positives and true negatives) among the total number of cases examined. As shown in Figure 11, XGBoost [7] has accuracy of 95.66% , indicating that it correctly classifies most instances. The proposed method uses RF model and demonstrates high accuracy of 95.34%, reflecting its robustness and reliability.

Precision (Positive Predictive Value, PPV) measures the proportion of positive identifications that were actually correct. As given in Figure 12 , ANN [2] has a precision of 99.79% suggesting it accurately identifies actual positives with minimal false positives. The proposed method with KNN has a precision of 99.21%, indicating its effectiveness in maintaining low false positive rates.

Recall (Sensitivity, True Positive Rate) measures the pro-

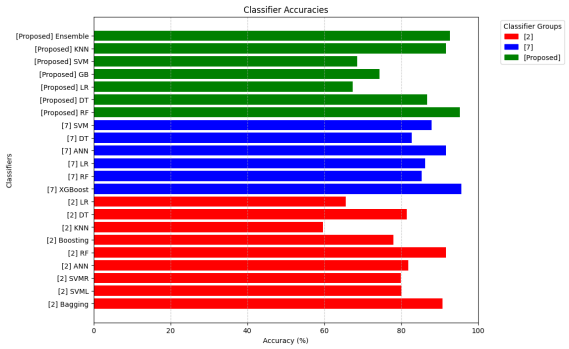


Figure 11: Comparative analysis with respect to accuracy

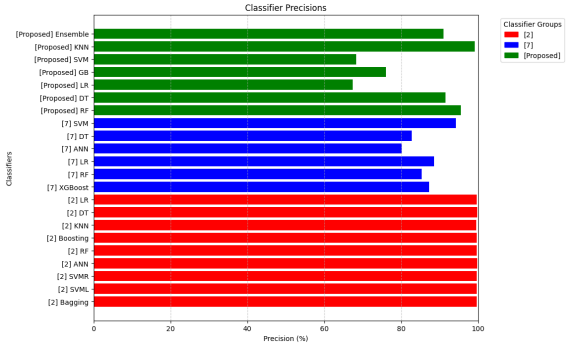


Figure 12: Comparative analysis with respect to precision

portion of actual positives that were correctly identified by the model. From Figure 13, it can be observed that proposed method (SVM model) with a recall of 99.01% excels in identifying almost all actual positive cases, which is crucial for detecting bankruptcy risks. Also, the proposed method with RF model and Ensemble model shows a high recall of 97.56% and 98.94% respectively, ensuring that most true positives are identified.

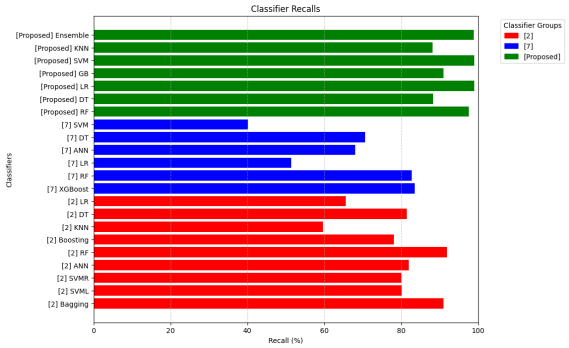


Figure 13: Comparative analysis with respect to recall

The F1 Score is the harmonic mean of precision and recall, providing a balance between the two metrics. As shown in Figure 14, the proposed method with RF model has F1 score of 96.57% demonstrates exceptional balance and overall performance, making it a strong choice for predicting corporate bankruptcy. Also the proposed Ensemble model has F1 score of 94.81% that shows a well-rounded performance.

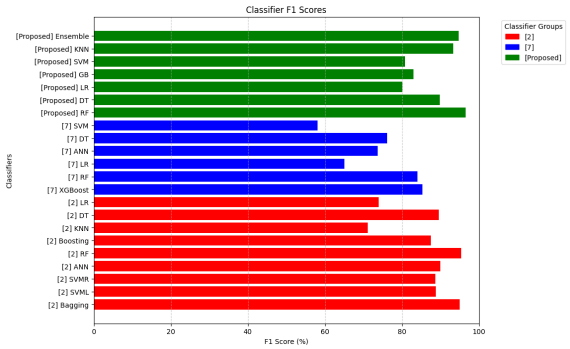


Figure 14: Comparative analysis with respect to F1-score

A primary constraint associate with the proposed methodology is its reliance on historical financial indicators, which may not fully account for sudden economic shifts or unprecedented events like the COVID-19 pandemic. This dependence limits the model's predictive accuracy in capturing abrupt financial distress signals, as it assumes historical patterns will continue in the future. Future work could explore integrating external economic indicators or real-time data sources to address these limitations and improve adaptability to sudden market shifts.

5 Conclusion

In conclusion, the proposed approach represents a significant advancement in the field of bankruptcy prediction, effectively addressing critical limitations observed in existing models. Through the strategic integration of advanced machine learning techniques, our methodology introduces a flexible and responsive system capable of accurately assessing bankruptcy risk. Key financial metrics such as the Altman Z-Score, Quick Ratio and Debt-to-Equity Ratio, complemented by Explainable AI Techniques, enhance transparency and interpretability, providing stakeholders with valuable insights for informed decision-making regarding corporate financial health.

Looking ahead, there is ample room for further refinement and optimization of the machine learning model to achieve even greater predictive accuracy. This entails exploring additional financial indicators and economic factors to strengthen the robustness of the bankruptcy prediction system. Additionally, alternative machine learning algorithms and ensemble methods will be thoroughly investigated to compare and optimize performance, ensuring the continued effectiveness of the proposed approach in real-world scenarios. Such endeavours are crucial for maintaining the relevance and practical applicability of the methodology in addressing the evolving challenges of financial risk management across diverse industries.

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A Novel Fuzzy C-Means Clustering Framework for Accurate Road Crack Detection: Incorporating Pixel Augmentation and Intensity Difference Features

Munish Bhardwaj[1], Nafis Uddin khan[2], Vikas Baghel[1]
[1]Jaypee University of Information Technology, Solan, India
[2]Department of Artificial Intelligence & Data Science, Faculty of Science and Technology(IcfaiTech), ICFAI Foundation for Higher Education(IFHE), Hyderabad, India
munish368@gmail.com, nafisuk@ifheindia.org, vikas.baghel@juit.ac.in

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The widespread occurrence of fractures in roads globally threaten traffic safety and demand substantial annual maintenance costs. Expenses can be substantially reduced by detecting fractures promptly, however manual methods are less rapid and inaccurate. Although automatic crack detection offers efficiency, but challenges like low contrast and background noise in pictures can impact its accuracy. To address these obstacles, this study proposes a potent Fuzzy C-Means clustering technique to enhance automated fracture detection. This approach employs pixel augmentation through a scaling factor to improve pixel details by examining the ratios from individual to cumulative values. Additionally, it considers the sum of the total ratio value and the minimum-to-maximum intensity within a 3x3 window, prior to segmentation. Moreover, the method identifies intrinsic pixel connections through absolute intensity differences, supporting crack detection. It also effectively detects cracks from unfamiliar images across diverse scenarios, without the need for a training dataset. According to experimental results, an enhanced Fuzzy C-Means Clustering approach for road crack detection, achieving superior precision, recall, and F1 scores (86.68, 88.53, 87.59) compared to K-Means Clustering (76.82,78.05,77.43), Fuzzy C-Means Clustering (79.76,80.72,80.23), and Manhattan distance based fuzzy C-Means clustering (84.09, 86.14,85.10). Additionally, it also reduces iteration counts, ensuring computational efficiency. These results validate its robustness and effectiveness, making it a promising solution for automated road crack detection systems.

Povzetek: Predlagan je nov okvir gručenja Fuzzy C-Means (FCM) za natančno zaznavanje razpok na cestah, ki vključuje povečanje slikovnih pik in značilnosti razlike v intenzivnosti. Ta pristop izboljšuje podrobnosti slikovnih pik z uporabo faktorja skaliranja in upošteva razliko v intenzivnosti med slikovnimi pikami. Predlagana metoda učinkovito zazna razpoke na različnih cestnih slikah brez potrebe po učnem naboru podatkov in dosega boljšo natančnost v primerjavi s tradicionalnimi metodami gručenja.

1 Introduction

Cracks impair the operation of roads and are often caused by decades of age, terrain or topographical conditions, and excessive traffic. Hence, it becomes imperative to acquiring precise statistics on road fractures [1], which can be accomplished using either hand-executed or automated process. The process of manually recognising fractures is tedious and prone to errors. It is therefore essential to proliferate automatic fracture recognising protocols. These automated methods provide crack information more quickly and precisely [2][3][4]. In addition, these automated methods may also be utilised to find fractures in a range of infrastructure such as hills, underground passageways, reservoirs, and Viaducts [1]. Therefore, to develop an algorithm for automatic road crack detection from images, a comprehensive understanding of how to identify road fractures in photographs is vital.

The crack detecting technique is representing in Figure 1 (road image taken from self-collected dataset). To initiate this approach, take photographs of the road portions where fractures are expected to be discovered with a camera or similar instrument [2]. Pre-processing should then be applied to the captured photos. The goal of pre-processing is to get rid of any unwanted components from the photographs that can degrade their quality. These artifacts can be eliminated, allowing for speedy and effective further processing of the image. The image must be converted to grayscale as one of the basic pre-processing stages. After this conversion is finished, a variety of filtering methods can be used to successfully remove unnecessary pixels. After the pre-processing phase, segmentation is applied to the images. In order to extract the precise features of interest from the raw photos, image segmentation is a vital step. There are many picture segmentation methods that are effective in separating regions with the same pixel characteristics [5]. Thus, clustering is found to be

the best technique for separating comparable pixels from raw images that indicate the existence of specific traits of interest [5][6].

Therefore, the utilization of clustering techniques, such as K-means clustering (KMC) approach [7][8], the fuzzy C-means clustering (FCMC) method [9][4], Manhattan distance based fuzzy C-Means clustering (MHFCM) algorithm [10] will enable the extraction of road crack patterns from images, as further elucidated in Section II.

Therefore, based on the insights gained from these studies, the primary objective of the proposed approach is to develop an innovative and robust FCM clustering (PIEFCMC) approach that can autonomously identify fractures.

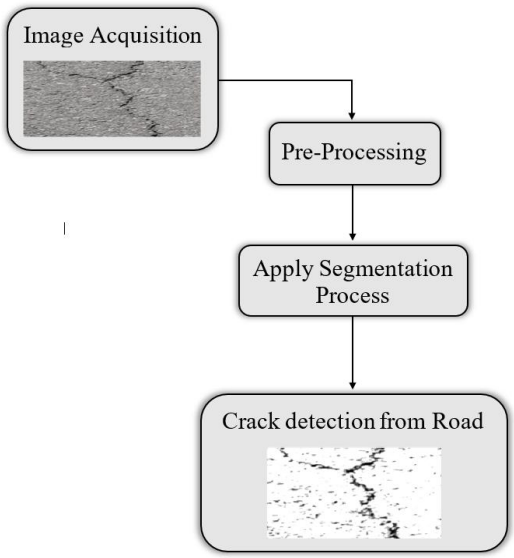


Figure 1. Architecture for road cracks identification utilizing the Image processing Techniques

This is accomplished through the pixel augmentation in 3×3 window and absolute intensity difference between maximum and minimum pixel values which enabling the detection of cracks even in images with low contrast. The suggested approach has been evaluated on a diverse range of road crack photos supplied from a self-compiled dataset. This method's key contributions are as follows:

1) The 2-D road pictures data have been processed into 3×3 window ($\widetilde{\mathcal{W}}_{d(3\times3)}$) and it spans on the entire picture.
2) The pixel augmentation ($\mathbb{P}_{aug}$) technique has been applying on each window. It utilizes each individual pixel by considering the sum of all values of its neighboring pixels with in $\widetilde{\mathcal{W}}_{d(3\times3)}$.
3) In instances where the original pixel values are minimal or approaching zero, the utilization of the total ratio value ($\vartheta_{\widetilde{\mathcal{W}}_{d(3\times3)}}$) serves to accentuate them against the backdrop of background noise.
4) Furthermore, the incorporation of the absolute difference enables this methodology viable the exploration of the inherent correlation between the pixels within the road images.
5) The outcomes of the experiments exhibit that the suggested robust FCM segmentation approach surpasses KMC, FCMC, and MHFCM in recognizing alligator, transverse, longitudinal fractures, and potholes in real-world road imagery.

The subsequent sections of this paper follow this organization: Section 2 presents a discussion of K-Means, FCM algorithms, and their respective variations. Section 3 elaborates on the proposed algorithm, offering detailed insights. Section 4 showcases the experimental results and discussions, and Section 5 serves as the concluding part of our study and future scope.

2 Related work

A brief overview of conventional and sophisticated FCMC, as well as associated current techniques for road crack identification, are provided in this section

2.1 Fuzzy-C-Means clustering (FCMC)

The FCMC algorithm, devised by Bezdek et al., [9][4] stands as a prominent approach in photo segmentation, leveraging an iterative unsupervised learning approach reminiscent of K-means clustering [12]. In settings devoid of noise, FCM outperforms by endowing every data point with a membership degree across clusters, ultimately determining final cluster values through a combination of centroid proximity and membership strength, ensuring a normalized distribution of memberships [12]. Hence the fundamental functions of the conventional FCMC algorithm can be encapsulated as below [12][23][24]:

1. The objective function of FCM as follows [10]:

$$\mathcal{T}_f(\phi, G) = \sum_{g=1}^{t}\sum_{l=1}^{p}\phi_{lg}^{b}\left\|\mathcal{X}_l - G_g\right\|^2 \quad (1)$$

Where $\mathcal{X}_l$ is finite dataset, p,t is total pixels, clusters, b is fuzzification parameter and G is cluster centers.

2. At the outset the membership matrix (ϕ_{lg}) undergoes random initialization via:$\sum_{g=1}^{t}\phi_{lg}(=1)$; where $\phi = \left[\phi_{lg}\right]_{t\times p}$ with $0 \le \phi \le 1$.

3. Utilize the following equation ascertain G_g

$$G_g = \frac{\sum_{l=1}^{p}\phi_{lg}^{b}*\mathcal{X}_l}{\sum_{l=1}^{p}\phi_{lg}^{b}};\ g=1,23,....t \text{ and } b>1 \quad (2)$$

4. Enhance the ϕ_{lg}& compute the updated ϕ_{lg} using:

$$\phi_{lg} = \frac{\left[\frac{1}{E_{lg}}\right]^{\frac{1}{b-1}}}{\sum_{c=1}^{t}\left[\frac{1}{E_{lc}}\right]^{\frac{1}{b-1}}} \quad (3)$$

Where E_{lg} is Euclidean distance ($E_{lg} = \|\mathrm{X}_l - G_g\|$)

5. The iterative procedure terminates once the $\|\phi^{(j+1)} - \phi^{(j)}\|$ become smaller than the positive threshold, denoted as Ω. Here, *j* is iteration index.

FCMC algorithms perform admirably in segmenting noise-free photographs but grapple with challenges when confronted with pictures noise and artifacts [12]. This is primarily due to their oversight of nearby pixel relationships, leading to difficulties in managing enumeration time costs [12].

2.2 Utilize in road crack reorganization

The manual road crack detection proves tedious and error-prone, emphasizing the necessity for an algorithm capable of precisely identifying fractures in unseen images amidst varying environmental conditions. FCMC's rise in popularity as an unsupervised clustering technique is evident in its widespread use across diverse image segmentation tasks, demonstrating superior fracture detection in newly captured photos across various environments. Nonetheless, the scarcity of FCMC-based algorithms for automated road fracture detection through photograph segmentation persists. A technique for recognizing cracks in concrete images has been demonstrated by Noh et al. [11]. It involved the utilization of FCMC and multiple noise scarcity strategies for segmentation. However, when considerable noise is present in cluster containing fractures, the accomplishment rate of fracture diagnosis drop significantly. Bhardwaj et al. [12] proposes an advanced FCMC algorithm that automatically detects fractures by incorporating optimal edge pixels using second-order differences and intensity-based fuzzy factors. By utilizing edge and non-edge pixel intensities, the method reliably identifies edges in low-contrast images without the need for training datasets or complex parameter tuning. It effectively detects fractures and surpasses existing methods.

Oumaa et al. [13] apply a multi-scale wavelet transform filtering method to reduce background noise and enhance image smoothness. Subsequently, they implement an improved process for identifying and segmenting potholes, utilizing unsupervised FCMC and morphological refinement techniques. Additionally, their methodology showcases precision in predicting the dimensions and forms of potholes.

Bhar. et al. [10] utilize the MHFCM approach, as elucidated in reference [10], integrating Manhattan distance (d_{Mht}) and histogram equalization (h_{eqn}) within the FCMC framework. The incorporation of d_{Mht} facilitates enhanced precision by evaluating dissimilarity between the dataset and cluster centroids, particularly enhancing cluster differentiation. Moreover, the inclusion of h_{eqn} contributes to enhancing overall photograph contrast. Consequently, this refined FCMC methodology demonstrates efficacy in detecting various types of road fractures in images. The representation of d_{Mht} and h_{eqn} is denoted as:

$$(d_{Mht})_{lg} = |x_l - G_g| \quad (4)$$

Whereas $g = 1,2,3,\ldots, t$ and $l = 1,2,3,\ldots, p$

$$h_{eqn}(S) = P(x_S) = \frac{T_S}{p} \; ; \; 0 \leq S \geq m\text{-}1 \quad (5)$$

Whereas *m* and *p* are the total number of gray levels and total number of pixels. The T_S is the total number of pixels with the same intensity level *S*.

While the MHFCM demonstrates adeptness in detecting fractures, it is encumbered by several limitations. Notably, the h_{eqn} procedure operates on the entire image, augmenting overall contrast but potentially sacrificing local information near edges and boundaries. Additionally, both FCM and h_{eqn} require parameter fine-tuning for optimal outcomes, thereby introducing processing challenges within the MHFCM framework. The amalgamation of these processes could exacerbate complexity and prolong processing times, particularly when dealing with large-scale images.

2.3 Other techniques

KMC necessitates a predetermined number of clusters, a task that can be challenging when dealing with intricate or high-dimensional data, as outlined by Bhard et al. [8]. The author Sadia et al. [14] present the road surface cracks are an early sign of pavement deterioration, leading to costly repairs. An automated method using color histogram analysis, K-means clustering, and Otsu thresholding segment 2D road images to detect cracks. The approach effectively reduces noise, preserves edges, and ensures accurate crack detection. Amita at al. [15] the study enhances image quality under overexposed and underexposed conditions by optimizing pixel intensity, entropy, noise, and edge details using a fuzzy approach. Images are mapped to fuzzy sets, and pixel intensity plays a key role in determining membership during fuzzification. The method preserves details, manages uncertainties, and controls sharpness to balance enhancement and noise reduction, ensuring improved visual quality. Cubero et al. [16] introduce novel approaches for swiftly extracting road fractures and illustrate the utilization of this technique to extract essential attributes required for highlighting the fractures. Ultimately, an image is classified employing a decision tree heuristic method.

By comprehending the basic structural characteristics of cracks, Shi et al.'s automated method [17] effectively reduces noise when identifying road fractures. The author Abdulrahman et al. [18] represent the system employs advanced image pre-processing, precise feature extraction, and a robust fuzzy inference mechanism to detect and classify cracks with exceptional accuracy and reliability across key performance metrics. For fracture detection, Wang et al. [19] state that pavement image quality is critical. But

these photos frequently have shadows or noises that mimic shadows, which can be from telegraph poles,

Table 1: Summarized the relevant studies related to road crack detection

Sr. No.	Author	Technique	Methodology	Dataset Used	Performance matrix	Key Findings
1.	Wang et al. [4]	Clustering Algorithms	This study evaluates clustering algorithms for pavement crack segmentation, finding mean-shift excels in de-noising under Gaussian noise based on NMI values.	From Internet Sources	RI-Mean :0.6030, NMI- Mean: 0.1529	Algorithms evaluated are sensitive to noise, leading to over-segmentation and misclassification.
2.	Bhard. et al. [10][5]	MHFCMC	The approach incorporates the integration of Manhattan distance and histogram equalization into FCMC.	From online sources	PSNR: 14.26, Execution Time:2.3	Lose local data close to borders and computational complexity
3.	Noh et al. [11]	Fuzzy C-means Clustering	This method employs segmentation, filtering, and morphological operations to remove noise and clutter using masks.	Self-Collected data set	Precision:0.9, Recall:0.8	Accurate identification is hampered by noise-rich fracture clusters.
4.	Oumaa et al. [13]	Fuzzy C-Means clustering and morphological reconstruction	It integrates multiscale texture-based wavelet filtering with superpixel clustering using FCMC and morphological reconstruction for pothole detection	Self-collected data set	Dice coefficient: 87.5%, Jaccard Index: 77.7%, Sensitivity: 97.6%	It depends on lighting conditions and visual obstructions, which may affect detection accuracy.
5.	Shi et al. [17][5]	Crack Forest	This method combines integral channel features, random structured forests, and a novel crack descriptor for improved detection and noise differentiation.	CFD dataset	Precision:0.8228, Recall: 0.8944, F1 Score: 0.8571	Incapable of precisely extracting complex background fractures.
6.	Chen et al. [21][5]	MANet	MANet uses MobileNet, depth wise convolutions, and hybrid attention to enhance feature importance.	Crack500 and CFD	Precision:0.7634, Recall:0.890, F1 Score: 0.8221	Longer computing times correspond to more complexity.

edifice, foliage, lights/ lamps, and other objects. An image processing technique is presented to overcome this difficulty and extract pavement fractures from shaded picture. Jie et al. [20] enhance the Canny algorithm with a bilateral filter, Sobel operator, and adaptive thresholds. Detection maps are refined morphologically and fused with DeepLabV3+ features to produce the final map. The Table 1 summarized the relevant studies discussed related to road cracks detection.

In order to overcome the limitations of existing methods, a methodology is required that employs a 3×3 window, along with scaling factor for pixel augmentation. This enhances pixel details and visibility prior to segmentation. Additionally, the local neighborhood relationship is used into the segmentation enhances feature extraction, reduces noise, improves clustering and boundary precision. These advanced aforementioned features are incorporated into the proposed algorithm, as detailed in Section 3.

3 Proposed method

In this section, we present a novel and useful method for spotting road fractures. In order to detect the road cracks, we have presented the innovative cracks identification method using Fuzzy C-Means Clustering i.e., PIEFCMC approach. The purpose of this approach is to address the limitations and issues with the existing methods covered in Section II. The Proposed method uses pixel augmentation ($\mathbb{P}_{aug}$) and absolute intensity difference ($\mathring{\mathrm{A}}_{d(max.,s)}(s)$). The $\mathbb{P}_{aug}$is crucial for preparing image data for analysis as it enhances finer details, making features more discernible. Therefore, in this approach a 3×3 window $(\widetilde{\mathcal{W}}_{d(3\times3)})$is utilize that spans the whole picture (represent in figure 2) along with scaling factor for pixel augmentation ($\mathbb{P}_{aug}$) which effectively emphasize pixels details. Additionally, the $\mathring{\mathrm{A}}_{d(max.,s)}(s)$ make this approach possible to observe the intrinsic connection between the picture pixels. As a result, it improves contrast between various region or objects in the picture, thereby enhancing clustering and boundary delineation, leading to improved outcomes. Hence, this process has been subtly represented in algorithm 1 & 2. The detail of the $\mathbb{P}_{aug}$of image using $\widetilde{\mathcal{W}}_{d(3\times3)}$ for PIEFCMC approach is discussed below:

3.1 3×3 Window

The 3×3 window plays a key role in examines the pixels within its frame and utilize them for pixel enhancement. As it slides across the image, it consistently utilized in the enhancement of each pixel, helping to highlight important features, and make cracks more pronounced. This process results in a clearer and more refined image, which is beneficial for tasks such as crack detection and segmentation. Therefore, it is imperative to ensure accuracy when creating this window. The relevant mathematical expression for the 3×3 window is as follows [22]:

$$\widetilde{\mathcal{W}}_{d(3\times3)} = \left[\dot{\mathrm{X}}_{\tilde{\alpha}+\ddot{\imath},\acute{\alpha}+\acute{\imath}}\right] \quad (6)$$

$$for\ \ddot{\imath} = g\ to\ g+2\ \&\ \acute{\imath} = d\ to\ d+2$$

$$for\ g = 0,1,2,3,\ldots..,l-2\ \&$$

$$d = 0,1,2,3,\ldots.,t-2$$

where as $\dot{\mathrm{X}}_{\tilde{\alpha}+\ddot{\imath},\acute{\alpha}+\acute{\imath}}$ represents the individual pixels in 3×3 window $(I_{Pixel(\widetilde{\mathcal{W}}_{d(3\times3)})})$, ï & í denote the row & column of the $\widetilde{\mathcal{W}}_{d(3\times3)}$, α̃&ά establish the beginning indices or offsets (*i.e.,* $\tilde{\alpha}\ \&\ \acute{\alpha} = 1$) and $l\ \&\ t$ is total number of rows & columns of the image. In particular, í stands for the columns to the right of ά and ï for the rows down from α̃. Together, α̃ and ά, ï and í identify an element's precise placement within the window.

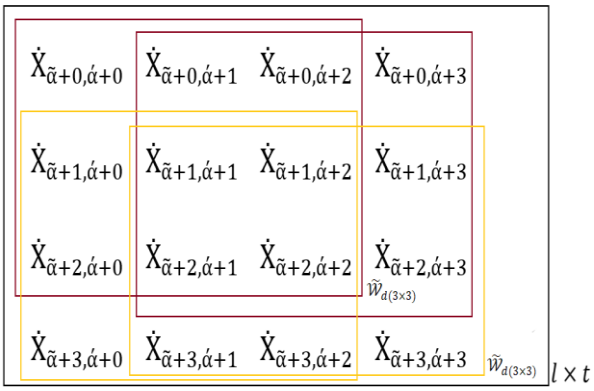


Figure 2: Representation of the 3×3 windows and its coverage of surrounding pixels

In Figure 2, the 3×3 window slides across the entire image $l \times t$ (l and t ranging from 0 to 3 for Figure 2), mentioned in table 2. It is also important to understand that the smaller windows (like 2×2), lack sufficient contextual information, making clustering sensitive to noise and ineffective at detecting continuous edges. Conversely, larger windows (4×4 or 5×5 etc.), tend to over-smooth the image, obscuring essential boundaries and fine details. Therefore, a 3×3 window strikes the right balance by reducing noise while preserving critical details, ensuring accurate segmentation and computational efficiency.

3.2 Pixel augmentation of the image using 3×3 Window

The Pixel augmentation approach is utilized to enhance the individual pixel values once the $\widetilde{\mathcal{W}}_{d(3\times3)}$ has been generated. The Figure 2 and Table 2 ensures that all pixels are covered by this window for pixel augmentation. However, the size of $l \times t$ may vary depending on the dimensions of the image being considered.

Table 2: Movement and coverage of the window based on g and d values

Step	Values of g and d for row (ï) and column (í)	Position of row (ï) and column (í)	Window Coverage
Initial Position	If $g = 0$ and $d = 0$	ï $= 0\ to\ 2$ & í $= 0\ to\ 2$	The Window covers the first 9 pixels
Horizontal Movement	If $g = 0$ and $d = 1$	ï $= 0\ to\ 2$ & í $= 1\ to\ 3$	The window shifts to the next column
Vertical Movement	If $g = 1$ and $d = 0$	ï $= 1\ to\ 3$ & í $= 0\ to\ 2$	The window moves to the next row
Complete Coverage	If $g = 1$ and $d = 1$	ï $= 1\ to\ 3$ & í $= 1\ to\ 3$	Window move to the next column and covering all pixels

However, necessary attention is required when determining the augmented scaling factor. Therefore, if the augmented scaling factor ($\tilde{\text{A}}\hat{\text{S}}_{\text{ƒ}a}$) is set excessively large, the picture may exhibit irregular or distorted appearances. While if setting excessively small can lose their precision and sharpness, resulting in a faded or obscured appearance. Therefore, adopting an optimal strategy is essential to maintaining edge quality and improves finer details, making features more visible. Thus, the mathematical expression for augmented image pixels ($\mathcal{X}_s$) are obtained by considering the values of augmented scaling factor ($\tilde{\text{A}}\hat{\text{S}}_{\text{ƒ}a}$) and individual image pixels $[\dot{\text{X}}_{\tilde{\alpha}+\ï,\acute{\alpha}+\acute{\text{í}}}]$, may be articulated in the following manner:

$$\mathcal{X}_s = [\tilde{\text{A}}\hat{\text{S}}_{\text{ƒ}a}] \times [\dot{\text{X}}_{\tilde{\alpha}+\ï,\acute{\alpha}+\acute{\text{í}}}] \quad (7)$$

The $\tilde{\text{A}}\hat{\text{S}}_{\text{ƒ}a}$ for $\widetilde{\mathcal{W}}_{d(3\times3)}$ is achieved by utilizing the following mathematical expression:

$$\tilde{\text{A}}\hat{\text{S}}_{\text{ƒ}a}=\ddot{\text{X}}_{\tilde{\alpha}+\ï,\acute{\alpha}+\acute{\text{í}}} = \left[\check{\text{R}}_{\widetilde{\mathcal{W}}_{d(3\times3)}} + \vartheta_{\widetilde{\mathcal{W}}_{d(3\times3)}}\right] \quad (8)$$

Whereas $\check{\text{R}}_{\widetilde{\mathcal{W}}_{d(3\times3)}}\left(=\frac{I_{Pixel(\widetilde{\mathcal{W}}_{d(3\times3)})}}{S_{um(\widetilde{\mathcal{W}}_{d(3\times3)})}}\right)$ is the ratio of individual pixel ($I_{Pixel(\widetilde{\mathcal{W}}_{d(3\times3)})}$) value to the sum of all pixels with in 3×3 window ($S_{um(\widetilde{\mathcal{W}}_{d(3\times3)})}$). The $Sum_{(\widetilde{\mathcal{W}}_{d(3\times3)})}$ is given as:

$$Sum_{(\widetilde{\mathcal{W}}_{d(3\times3)})} = \sum_{\ï=g}^{g+2}\sum_{\acute{\text{í}}=d}^{d+2} \dot{\text{X}}_{\tilde{\alpha}+\ï,\acute{\alpha}+\acute{\text{í}}} \quad (9)$$

$$for\ g = 0,1,2,3,\ldots..,l-2\ \&d = 0,1,2,3,\ldots.,t-2$$

Furthermore, the $\vartheta_{\widetilde{\mathcal{W}}_{d(3\times3)}}$ is the sum of Ŧ_{rv} and $\grave{\text{I}}_{min.,max.}$. Whereas the Ŧ_{rv} is the addition of total ratio value of $\check{\text{R}}_{\widetilde{\mathcal{W}}_{d(3\times3)}}$ in $\widetilde{\mathcal{W}}_{d(3\times3)}$ and $\grave{\text{I}}_{min.,max.}$ is the ratio of minimum to maximum intensity with in $\widetilde{\mathcal{W}}_{d(3\times3)}$. When $\mathcal{X}_s$ are obtained, then the use $\vartheta_{\widetilde{\mathcal{W}}_{d(3\times3)}}$ enhances their visibility, also helping them to stand out more from background or noise. Without applying $\vartheta_{\widetilde{\mathcal{W}}_{d(3\times3)}}$, the pixel values may reduce significantly or may tiny or almost zero. Therefore, algorithm 1 illustrates the process of pixel augmentation of an image using a 3×3 window.

Algorithm 1: Pixel augmentation using 3×3 window

1. Input: Image of size $l\times t$
2. Output: Augmented pixels $\mathcal{X}_s$using $\widetilde{\mathcal{W}}_{d(3\times3)}$
3. Initialization Parameters:
   a. Size of window is 3, row and column are represented with ï&íرespectively
4. Procedure:

- Start iteration:
  a. Outer Loop: Iterate over row (ï):
  ï $= g\ to\ g+2$ %% $g = 0,1,2,\ldots.,l-2$
  b. Inner Loop: Iterate over columns (í):
  í $= d\ to\ d+2$ %% $d = 0,1,2,\ldots.,t-2$
  c. Extract the current 3×3 window:
  $\widetilde{\mathcal{W}}_{d(3\times3)} = [\dot{\text{X}}_{\tilde{\alpha}+\ï,\acute{\alpha}+\acute{\text{í}}}]$ %% $Using\ eqn.(6)$
  d. Compute: $\check{\text{R}}_{\widetilde{\mathcal{W}}_{d(3\times3)}}$, $Sum_{(\widetilde{\mathcal{W}}_{d(3\times3)})}$ and $\vartheta_{\widetilde{\mathcal{W}}_{d(3\times3)}}$
  e. Compute the augmented scaling factor:
  $\tilde{\text{A}}\hat{\text{S}}_{\text{ƒ}a}=\ddot{\text{X}}_{\tilde{\alpha}+\ï,\acute{\alpha}+\acute{\text{í}}} = \left[\vartheta_{\widetilde{\mathcal{W}}_{d(3\times3)}} + \check{\text{R}}_{\widetilde{\mathcal{W}}_{d(3\times3)}}\right]$
  f. Compute the final augmented pixel's values:
  $\mathcal{X}_s = [\tilde{\text{A}}\hat{\text{S}}_{\text{ƒ}a}] \times [\dot{\text{X}}_{\tilde{\alpha}+\ï,\acute{\alpha}+\acute{\text{í}}}]$ %% $Using\ eqn.(7)$
- Complete iteration:
  a. The window automatically shifts by incrementing í within the inner loop
  b. After completing a row, increment ï to move to next row
  c. The algorithm terminates when last column (í $= d\ to\ d+2$) and last row (ï $= g\ to\ g+2$) are reached or processed

5. The result represents the augmented pixels ($\mathcal{X}_s$) for complete image $l\times t$. Further these pixels applied in segmentation process.

The Pixel augmentation enhances the visual quality of road images, improving their clarity and detail. By boosting contrast, emphasizing edges, and preserving essential features, it makes road cracks more distinguishable. This pre-processed image is subsequently input into PIEFCMC, facilitating a more precise distinction between crack and non-crack regions. This process reduces false positives and ensures consistent segmentation accuracy, even in the presence of noise, uneven lighting, and surface irregularities.

3.3 Exhaustive description of the PIEFCMC

The objective function (ℶ) of the reliable & effective PIEFCMC approach for the successful identification of road fractures can be articulated as follows:

$$\text{ℶ}(\psi, \text{ℽ}) = \sum_{e=1}^{\text{ŭ}} \sum_{s=1}^{m} \psi_{es}^{c} \times \|\mathcal{X}_s - \text{ℽ}_e\|^2 \times \text{Å}_{d(max.,s)}(s) \quad (10)$$

where ŭ&m stand for the number of clusters for partitioning the data and pixels in a picture, $\mathcal{X}_s$ represent the augmented image pixels, ℽ_e is cluster center, c is fuzzification parameter ($(c > 1)$ and controls the degree of cluster overlap), ψ_{es} is the fuzzy membership matrix quantify the degree to which each data point belongs to each cluster. The $\text{Å}_{d(max.,s)}(s)(= |\mathcal{X}_{max.} - \mathcal{X}_s|)$ stands for absolute intensity difference between maximum pixel intensity and all the other pixels.

The utilization of the $\text{Å}_{d(max.,s)}(s)$function enables the proposed algorithm possible to observe the intrinsic connection between the pixels in $l \times t$picture. It measures how each pixel deviates from the most prominent intensity, establishing a relative scale of connection. This process help in grouping similar pixels, while isolating dissimilar ones, thereby reducing noise, enhances clarity, ultimately improving segmentation accuracy.

After that employing *Lagrange multiplier method* to reducing the objective function $\text{ℶ}(\psi, \text{ℽ})$, that may ascertain the revised membership degrees and cluster centers in PIEFCMC, as follows:

$$\zeta_{multiplier} = \sum_{e=1}^{\text{ŭ}} \sum_{s=1}^{m} \psi_{es}^{c} \times \|\mathcal{X}_s - \text{ℽ}_e\|^2 \times \text{Å}_{d(max.,s)}(s) + \sum_{s=1}^{m} \nabla \left(1 - \sum_{e=1}^{\text{ŭ}} \psi_{es}\right) \quad (11)$$

Utilizing partial derivative on $\zeta_{multiplier}$ with regards to ψ_{se}^{c} & subsequently setting it to zero, we arrive:

$$\psi_{es} = \left(\frac{\nabla}{c(\|\mathcal{X}_s - \text{ℽ}_e\|^2 \times \text{Å}_{d(max.,s)}(s))}\right)^{\frac{1}{c-1}} \quad (12)$$

Utilizing the $\zeta_{multiplier}$ derivative in relation to the ∇ (Lagrange multipliers), the following results are obtained:

$$\frac{\partial \zeta_{multiplier}}{\partial \nabla} = \sum_{e=1}^{\text{ŭ}} \psi_{es} - 1 = 0 \quad (13)$$

To ascertain the membership function, solve the eqn. no. 12-13 and yield the following result:

$$\psi_{es} = \frac{\left[\frac{1}{\partial_{es}}\right]^{\frac{1}{c-1}}}{\sum_{\text{ƒ}=1}^{\text{ŭ}} \left[\frac{1}{\partial_{\text{ƒ}s}}\right]^{\frac{1}{c-1}}} \quad (14)$$

Likewise, obtaining the cluster centroid's the partial derivative of $\zeta_{multiplier}$ with regard to ℽ_e is provides as:

$$\frac{\partial \zeta_{multiplier}}{\partial \text{ℽ}_e} = 0 \quad (15)$$

After the aforementioned equation is extricate, the centroid is eventually obtained as follows:

$$\text{ℽ}_e = \frac{\sum_{s=1}^{m} \psi_{es}^{c} \times \mathcal{X}_s \times \text{Å}_{d(max.,s)}(s)}{\sum_{s=1}^{m} \psi_{es}^{c}} \quad (16)$$

The algorithm 2 is on PIEFCM clustering are given below:

Algorithm 2: PIEFCM clustering algorithm

1. Input: Size of image $l \times t$
2. Output: *%% Identification of the cracks on road*
3. Initialization Parameters:
   a. ŭ is number of clusters, $\mathcal{X}_s$ represent the augmented image pixels, m is the total number of pixels in picture,ℽ_e is cluster center, c is fuzzification parameter, ψ_{es} the fuzzy membership matrix
4. Procedure:
   4.1. Outer Loop (e): Iterate for ŭ *%% Start iteration over cluster*
   4.2. Inner Loop (s): Iterate for m *%% Start iteration over pixels*
   4.3. Membership matrix is randomly initialization in the beginning: $\psi_{es} = 1$ $\%\%\boldsymbol{\psi} = [\psi_{es}]_{\text{ŭ}\times m}$ *with* $0 \leq \psi_{es} \leq 1$
   4.4. Exit inner loop: When *s=m; %% Stop iterating over pixels*
   4.5. Exit outer loop: When *e=*ŭ; *%% Stop iterating over clusters*
   4.6. Initialize: *ÿ=0 %% ÿ=iteration index*
   4.7. Outer Loop (e): Iterate for ŭ *%% Start iteration over clusters*
   4.8. Inner Loop (s): Iterate for m *%% Start iteration over pixels*

4.9. Compute γ_e: $\gamma_e = \frac{\sum_{s=1}^{m} \psi_{es}^{c} \times \mathcal{X}_s \times \text{Å}_{d(max.,s)}(s)}{\sum_{s=1}^{m} \psi_{es}^{c}}$ %% $\text{Å}_{d(max.,s)}(s)(= |\mathcal{X}_{max.} - \mathcal{X}_s|)$

4.9.1. Condition: For $\text{Å}_{d(max.,s)}(s)$ *%% Absolute intensity difference*

4.9.1.1. If $\text{Å}_{d(max.,s)}(s) \neq 0$; then

$\text{Å}_{d(max.,s)}(s) = |\mathcal{X}_{max.} - \mathcal{X}_s|$

else $(\text{Å}_{d(max.,s)}(s) = 0)$

$\text{Å}_{d(max.,s)}(s) = A_v(\mathcal{X}_{max.}, \mathcal{X}_s)$ *%% Average (A_v) between* $\mathcal{X}_{max.}$ *and* $\mathcal{X}_s$

4.10. Calculate and update ψ_{es}:

$$\psi_{es} = \frac{\left[\frac{1}{\partial_{es}}\right]^{\frac{1}{c-1}}}{\sum_{\text{ƒ}=1}^{\text{ʊ}} \left[\frac{1}{\partial_{\text{ƒ}e}}\right]^{\frac{1}{c-1}}}$$

%% $\partial_{es} = \|\mathcal{X}_s - \gamma_e\|$

4.11. Exit inner loop: When *s=m; %% stop iterating over pixels*

4.12. Exit outer loop: When *e*=ʊ; *%% stop iterating over clusters*

4.13. Repetation or convergence criteria: Increment $\text{ÿ} = \text{ÿ} + 1$ or revisit steps 4.7 until an identical $\gamma_e$emerges, or Max. $\left\|\boldsymbol{\psi}^{(\text{ÿ}+1)} - \boldsymbol{\psi}^{(\text{ÿ})}\right\| < \alpha$, where α is positive threshold termination criteria.

5. Output: Cracks identification from complete $l \times t$image

4 Experimental result and analysis

This section analyses and juxtaposes /compares the outcomes of the PIEFCMC method with a number of other methods that are implemented in Matlab, such as KMC, FCMC, MHFCMC. A central processing unit (CPU) of Intel Core i7, 1.80 GHz of clock speed, Random-access memory (RAM) of 8.00 GB, and Microsoft Windows 11 Pro are the specifications of the personal computer (PC) used for this assessment. The performance of the suggested approach is primarily influenced by the parameters *c* and ʊ, which have been assigned values of 2 each. Therefore, by using these parameters, fractures may be clearly distinguished among their adjacent regions during the detecting procedure. This facilitates a clear division into two clusters: one for crack areas and the other for non-crack regions. Consequently, all variations of the fuzzy algorithms in our simulation operate under these similar conditions.

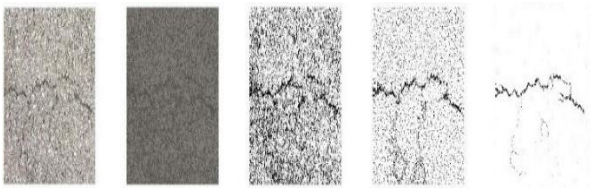
In this simulation a numerous number of road photos exhibiting numerous varieties of flaws and fractures, including transverse crack ($\check{\text{T}}_{crk}$), longitudinal crack (Ł_{crk}), alligator fractures ($\check{\text{A}}_{crk}$) and pathole ($\acute{\text{P}}_{\text{ôł}}$). Excessive exhaustion and insufficient articulation cause the Ł_{crk} to emerge longitudinally along the road [16]. When an articulation is positioned within a vicinity wherein the road endures to intense stress, a $\check{\text{T}}_{crk}$may emerge. $\check{\text{A}}_{crk}$ may appear mainly due to inadequate strength in the asphalt substrate. When precipitation penetrates the earth underlying the roadway's exterior and expands and contracts, it impacts substantial structural degradation in the form of $\acute{\text{P}}_{\text{ôł}}$ [13]. Hence for crack types, we personally gathered the dataset from National Highway (NH)-154 in Himachal Pradesh, India, from whence these pictures are taken. Samsung's 64-megapixel camera was used to take these photos.

The suggested procedure has been contrasted to anterior methods, specifically KMC [7][8], FCMC [9][4], and MHFCMC [10]. Utilising self-gathered datasets consists of non-tainted and tainted road photos, PIEFCMC performs more effectively in terms of number of iterations, precision, recall, and F1 Score.The superior performance of this can be attributed to its innovative use of pixel enhancement and absolute intensity difference in segmentation process, as discussed in Section 3. This unique approach effectively reduces noise and improves the clarity and visibility of detected road cracks, offering a significant advantage over K-Means, FCMC, and MHFCMC, whose limitations are outlined in Section 2.

Additionally, we recognize that no method is flawless. Hence, PIEFCMC may also faces performance limitations in the situations where road cracks are extremely faint or image quality is highly compromised or instances of severe occlusion. Therefore, the experimental analysis is explained in detail in subsections *4.1 and 4.2*, respectively, offering a description of the empirical outcomes for the two aforementioned photo genres.

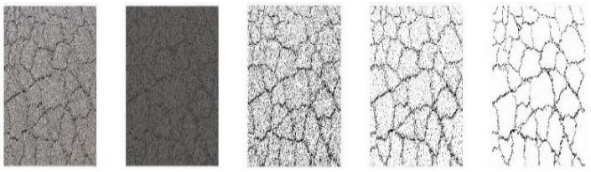
4.1 Non-Tainted images of road

A non-contaminated road crack image is free from oil stains, paint, mud, and other obstructions for analysis. The analysis contrasts the KMC, FCMC, MHFCMC, and PIEFCMC for the various visual formats shown in Figures 3(a), 4(a), 5(a), and 6(a). In juxtaposition with MHFCMC, KMC and FCMC yield inferior results for road fracture identification as shown in Fig. 3-6: (b-d). However, the MHFCMC displays relatively little disturbance and has trouble diagnosing fractures, shown in Fig. 3-6: (d)). Regarding noise, reliability, and iterations, the PIEFCMC approach's output (Fig. 3(e)–6(e)) offers superior and valuable results in lieu of the other methods. In addition, the PIEFCMC can distinguish between cracked and non-crack pixels with ease.



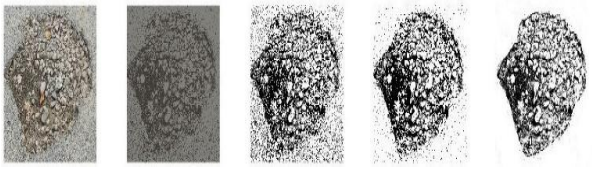
(a) (b) (c) (d) (e)

Figure 3. Detection results of $\check{T}_{crk}$: (a) Original image, (b) KMC, (c) FCMC, (d) MHFCMC, (e) PIEFCMC



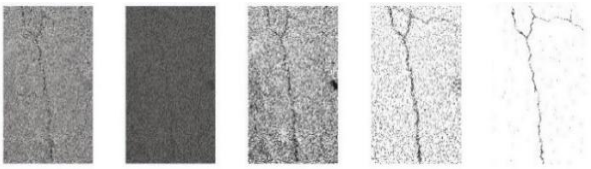
(a) (b) (c) (d) (e)

Figure 4. Detection results of $\check{A}_{crk}$: (a) Original image, (b) KMC, (c) FCMC, (d) MHFCMC, (e) PIEFCMC



(a) (b) (c) (d) (e)

Figure 5. Detection results of $\acute{P}_{\delta\text{ł}}$: (a) Original image, (b) KMC, (c) FCMC, (d) MHFCMC, (e) PIEFCMC



(a) (b) (c) (d) (e)

Figure 6: Detection results of $Ł_{crk}$: (a) Original image, (b) KMC, (c) FCMC, (d) MHFCMC, (e) PIEFCMC

Consequently, we used precision ($þ_{\delta n}$), recall ($\ddot{R}_{\acute{c}al}$), F1 score ($\mathcal{F}_{1\hat{r}\hat{e}}$) & number of iterations ($\mathcal{N}_{\bar{i}}$)to quantitatively describe the fracture reliability of the different strategies for multiple kinds of fracture pictures. With regard to Table 3, the following values of $þ_{\delta n}$, $\ddot{R}_{\acute{c}al}$, $\mathcal{F}_{1\hat{r}\hat{e}}$may be determined in accordance with true positive ($ŧ_p$), false positive ($\dot{f}_p$), and false negative ($\dot{f}_{\tilde{n}}$) data [12]:

$$þ_{\delta n} = \frac{ŧ_p}{ŧ_p + \dot{f}_p} \tag{17}$$

$$\ddot{R}_{\acute{c}al} = \frac{ŧ_p}{ŧ_p + \dot{f}_{\tilde{n}}} \tag{18}$$

$$\mathcal{F}_{1\hat{r}\hat{e}} = \frac{2X þ_{\delta n} X \ddot{R}_{\acute{c}al}}{þ_{\delta n} + \ddot{R}_{\acute{c}al}} \tag{19}$$

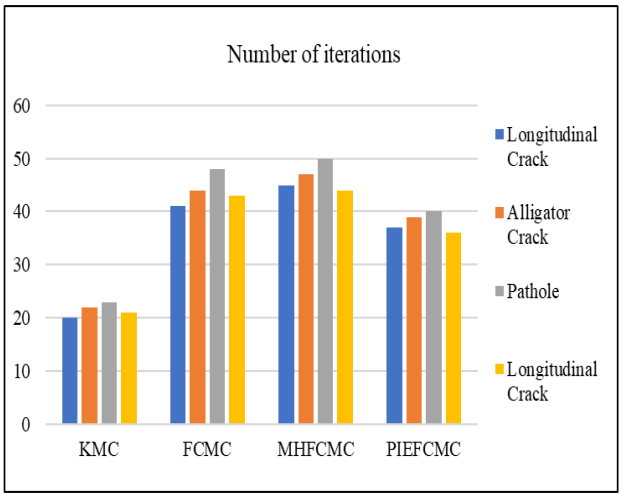


Figure 7: Number of iterations across multiple algorithms for detecting various kind of cracks in non-tainted images

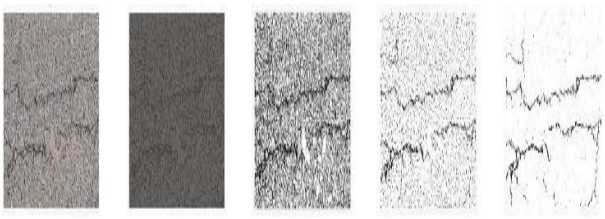
The PIEFCMC contain an efficient pixel augmentation with neighborhood relationshipoutperforms various other algorithm in terms of $þ_{\delta n}$, $\ddot{R}_{\acute{c}al}$, &$\mathcal{F}_{1\hat{r}\hat{e}}$for all sorts of fractures, hence offering effective information on fracture recognition. The KMC method boasts a shorter $\mathcal{N}_{\bar{i}}$ in comparison to its counterparts. However, the simulation results reveal its underperformance in terms of $þ_{\delta n}$, $\ddot{R}_{\acute{c}al}$, $\mathcal{F}_{1\hat{r}\hat{e}}$. Hence, based on the comprehensive findings presented in Table 3 and Figure 7, it is apparent that PIEFCMC demonstrates superior efficiency for $\mathcal{N}_{\bar{i}}$when compared with other's.

4.2 Tainted images of road

This section delves into the discussion of various categories of imperfections and fissures observed in photos of tainted roadways, including paint marks, mud and shadows, etc. The findings entail a comparison of several algorithms across varied visuals, as depicted in Figures 8(a), 9(a), 10(a), and 11(a). The findings indicate that MHFCMC outperforms the KMC and FCMC algorithms in terms of efficacy, as is evident in Figures 8–11 (b–d). As seen in Figures 8(d)–11(d), MHFCMC, however, exhibits significant shortcomings, including poor responsiveness, noise, shadow traces, and blurring, especially in comparison to PIEFCMC. The PIEFCMC approach surpasses comparable algorithms in regard of noise reduction, precision and execution time and identifies boundaries from the vicinity with efficacy.

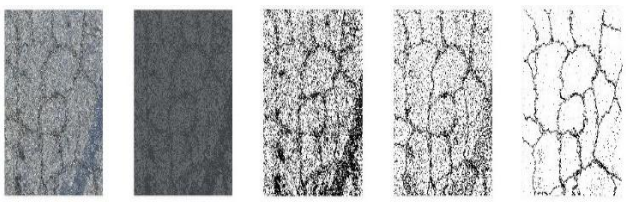
Table 3: Comparative analysis of crack identification performance between KMC, FCMC, MHFCMC and PIEFCMC for non-tainted images

Crack Types	Parameters	KMC	FCMC	MHFCM	PIEFCMC
$\check{T}_{crk}$	$þ_{ő n}$	74.07	78.57	83.90	85.95
	$\check{R}_{ćal}$	75.94	80.48	84.88	88.43
	$\mathcal{F}_{1\hat{r}\hat{e}}$	74.99	79.51	84.38	87.17
	$N_{\tilde{i}}$	20	41	45	37
$\check{A}_{crk}$	$þ_{ő n}$	76.82	79.76	84.09	86.68
	$\check{R}_{ćal}$	78.05	80.72	86.14	88.53
	$\mathcal{F}_{1\hat{r}\hat{e}}$	77.43	80.23	85.10	87.59
	$N_{\tilde{i}}$	22	44	47	39
$\acute{P}_{ől}$	$þ_{ő n}$	76.96	77.64	83.33	82.95
	$\check{R}_{ćal}$	78.39	75.86	81.39	85.88
	$\mathcal{F}_{1\hat{r}\hat{e}}$	77.66	76.73	82.34	84.38
	$N_{\tilde{i}}$	23	48	50	40
$Ł_{crk}$	$þ_{ő n}$	72.83	78.57	83.48	84.44
	$\check{R}_{ćal}$	75.64	80.48	85.97	86.36
	$\mathcal{F}_{1\hat{r}\hat{e}}$	74.20	79.51	84.70	85.38
	$N_{\tilde{i}}$	21	43	44	36



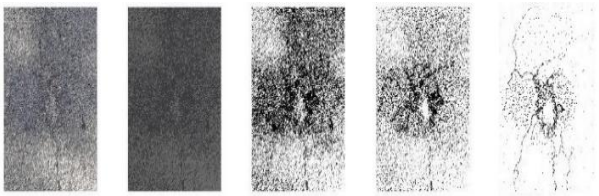
(a) (b) (c) (d) (e)

Figure 8: Detection results of $\check{T}_{crk}$: (a) Original image, (b) KMC, (c) FCMC, (d) MHFCMC, (e) PIEFCMC



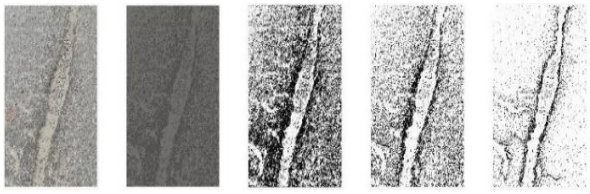
(a) (b) (c) (d) (e)

Figure 9: Detection results of $\check{A}_{crk}$: (a) Original image, (b) KMC, (c) FCMC, (d) MHFCMC, (e) PIEFCMC



(a) (b) (c) (d) (e)

Figure 10: Detection results of$\acute{P}_{ől}$: (a) Original image, (b) KMC, (c) FCMC, (d) MHFCMC, (e) PIEFCMC



(a) (b) (c) (d) (e)

Figure 11: Detection results of$Ł_{crk}$: (a) Original image, (b) KMC, (c) FCMC, (d) MHFCMC, (e) PIEFCMC

Table 4: Comparative analysis of crack identification performance between KMC, FCMC, MHFCMC and PIEFCMC for tainted images

Crack Types	Parameters	KMC	FCMC	MHFCM	PIEFCMC
$\check{T}_{crk}$	$þ_{ő n}$	71.12	76.84	80.40	82.51
	$\check{R}_{ćal}$	72.98	77.37	83.02	84.95
	$\mathcal{F}_{1\hat{r}\hat{e}}$	72.03	77.10	81.68	83.71
	$N_{\tilde{i}}$	22	42	46	38
$\check{A}_{crk}$	$þ_{ő n}$	72.67	76.05	81.76	83.32
	$\check{R}_{ćal}$	74.98	78.67	83.24	85.35
	$\mathcal{F}_{1\hat{r}\hat{e}}$	73.80	77.33	82.49	84.32
	$N_{\tilde{i}}$	24	46	49	40
$\acute{P}_{ől}$	$þ_{ő n}$	70.06	74.93	77.83	80.47
	$\check{R}_{ćal}$	68.35	72.49	79.18	82.93
	$\mathcal{F}_{1\hat{r}\hat{e}}$	69.19	73.68	78.49	81.68
	$N_{\tilde{i}}$	23	44	47	37
$Ł_{crk}$	$þ_{ő n}$	72.98	75.64	79.98	81.83
	$\check{R}_{ćal}$	73.57	77.59	81.48	83.47
	$\mathcal{F}_{1\hat{r}\hat{e}}$	73.27	76.60	80.72	82.64
	$N_{\tilde{i}}$	21	45	48	39

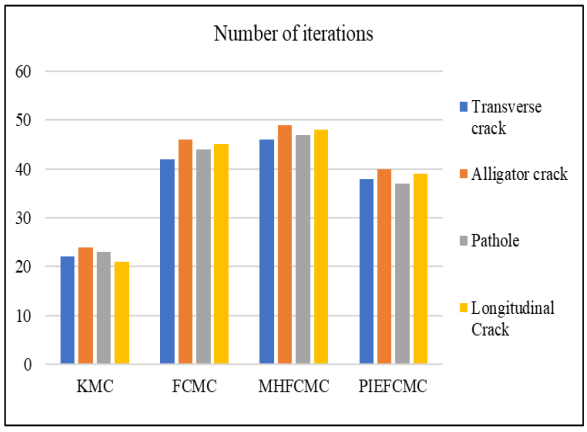


Figure 12: Number of iterations across multiple algorithms for detecting various kind of cracks in tainted images

The Equations 17-19 have been utilised in the current model for determining the $þ_{ôn}$, $Ř_{ćal}$ and $\mathcal{F}_{1îê}$ for crack accuracy; the outcomes are depicted in Table 4. The Table 4 indicates that PIEFCMC trumps all variants, allowing effective recognition of fractures in spite of tainted photos.

Additionally, the KMC approach executes more quickly than the others—including PIEFCMC—it performs noticeably worse overall. On the other hand, as Figure 12 illustrates, PIEFCMC provides an accurate, efficient and effective $Ɲ_{ĩ}$ for the entire operation then other.

4.3 Comparison between proposed PIEFCMC and Deep Learning based approaches

The proposed PIEFCMC algorithm offers several benefits over deep learning-based approaches such as Convolutional Neural Networks (CNNs). Unlike CNNs, which require large labeled datasets and high-performance hardware, PIEFCMC operates efficiently with smaller datasets [25] and standard hardware, such as a CPU. It has a substantially lower computational cost than CNNs. Additionally, CNNs require intensive and time-consuming training process, but PIEFCMC does not require a training phase. Additionally, CNNs are frequently limited in their interpretability [25], whereas PIEFCMC is extremely interpretable. However, CNNs can achieve higher accuracy and adaptability for complex patterns, especially when trained on diverse datasets, making them suitable for highly precise tasks [25][26]. Thus, PIEFCMC serves as a cost-effective and efficient alternative, especially in scenarios with limited resources or data.

4.4 Discussions

The experimental findings unequivocally demonstrate the efficacy of the proposed PIEFCMC algorithm in accurately detecting road cracks from both tainted and non-tainted images. This innovative approach employs a 3×3 window with a scaling factor for pixel enhancement, effectively utilizing absolute intensity differences to emphasize finer details while significantly mitigating noise. These features address critical limitations evident in previously reviewed methods, establishing PIEFCMC as a robust and effective solution.

In comparison, existing methods such as KMC, FCMC, and MHFCMC exhibit notable shortcomings that limit their effectiveness. KMC's reliance on pre-defined clusters hinders its adaptability to intricate data, compromising precision. FCMC, is highly susceptible to noise due to its disregard for spatial pixel connectivity, resulting in reduced reliability. MHFCM faces processing challenges, due to complexities associated with FCM and histogram equalization.

The superiority of PIEFCMC is particularly evident in its performance metrics. For tainted images, PIEFCMC achieves precision, recall, and F1 scores of 86.68, 88.53, and 87.59, respectively, outperforming KMC (76.82, 78.05, 77.43), FCMC (79.76, 80.72, 80.23), and MHFCMC (84.09, 86.14, 85.10). Similarly, for non-tainted images, PIEFCMC achieves precision, recall, and F1 scores of 83.32, 85.35, and 84.32, surpassing KMC (72.67, 74.98, 73.80), FCMC (76.05, 78.67, 77.33), and MHFCMC (81.76, 83.24, 82.49). These results highlight PIEFCMC's consistent accuracy and reliability across diverse image conditions.

Another significant advantage of PIEFCMC lies in its optimized iteration count. While KMC demonstrates the fewest iterations for tainted (21) and non-tainted (20) images, this efficiency comes at the cost of reduced segmentation accuracy. In contrast, PIEFCMC achieves a balance between iteration count and performance, requiring 37 iterations for tainted images and 36 for non-tainted images while delivering superior precision and reliability. FCMC and MHFCMC, on the other hand, require 41–46 iterations, further underscoring the computational efficiency of PIEFCMC.

In conclusion, PIEFCMC significantly advances the field of road crack detection by delivering higher precision, recall, and F1 scores while effectively addressing noise and computational challenges. Although it slightly lags behind KMC in iteration count, its superior segmentation accuracy, robustness, and consistency across varying image types validate its potential as a transformative approach in this domain.

5 Conclusion and future research directions

This study presents a novel and innovative method for road fracture identification based on FCM clustering. Despite the dearth of research on the application of the FCM algorithm to road crack identification. Still, this approach reduces the effect of noise and finds road fractures in images better than FCM and its variants. To achieve this, a 3×3 window is spans across the entire image. This approach enables the enhancement of pixel technique within each window, effectively emphasizing the finer details of cracks. By this method, each pixel in the 3×3 window is considered based on the sum of the

values of its neighboring pixels prior to segmentation. In situation, when initial pixel values are little or almost zero, $\vartheta_{\tilde{W}_{d(3\times3)}}$ helps draw attention to them by making them stand out contrary to noise or the backdrop, which improves contrast among various areas or entities in the picture. Furthermore, this strategy allows the observation of the intrinsic connection among the photograph's pixels because of the absolute difference. Consequently, the innovative methodology markedly enhances clustering, precision meticulously delineates boundaries, and effectively eradicates blurring, culminating in substantially superior outcomes. Even in images characterized by low contrast, it adeptly identifies cracks and edges. Unlike many FCM variations, the novel strategy eradicates the need for determining the crucial tuning parameters, and experimental results confirm that it consistently produces better results. Moreover, without the exigency to training dataset, the novel algorithm can accurately recognize fractures in novel, unseen images of diverse types. The comprehensive test findings demonstrate the effectiveness of the novel algorithm in terms of $þ_{\acute{o}n}, \hat{\tilde{R}}_{\acute{c}al}, \mathcal{F}_{1\hat{i}\hat{e}}$and iteration count. As a result, PIEFCMC exhibits exceptional effectiveness in identifying different types of road cracks, saving a substantial sum of money and effort.

The upcoming task entails installing a state-of-the-art online embedded device with premium webcams in cars. The gathering and accumulation of immediate video streams will be made possible by this upgrade. Furthermore, utilising real-time data streams, a customised methodology will be developed to determine the width and depth of road fractures. Also, the proposed method's performance under rainy conditions has not been considered in the current work due to the unavailability of datasets. Consequently, we have not utilized such images in any experiments. However, we intend to thoroughly explore this aspect in our future research. Moving forward, integrating PIEFCMC (an unsupervised machine learning approach) with other machine learning techniques could further improve the accuracy and robustness of road crack detection.

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Development and Evaluation of Machine Learning Models for Early Detection of Asymptomatic COVID-19 Patients Using Heart Rate and Oxygen Levels

Hafiz Haseeb Tasleem[1], Mueed Ahmed [1], Muhammad Waqar Arshad[1*], and Muhammad Hamza [2]
[1]Faculty of Computing, Riphah International University, Islamabad, Pakistan
[2]Faculty of Computing and IT, University of Sialkot, Sialkot, Pakistan
E-mail: hafizhaseebit@gmail.com, mueedahmed92@gmail.com, waqararshad211@gmail.com, muhammadhamzait9@gmail.com
[*]Corresponding author

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Since the coronavirus disease 2019 (COVID-19) spread across the world in late December 2019, it has caused significant harm and major challenges in over 190+ countries all over the world. The research that is being done today is getting all the chest X-ray images and lung images. With the help of this, researchers are predicting Covid-19. There is mounting evidence that many COVID-19 patients are asymptomatic or have only minor symptoms but may still spread the virus to others. In the existing system, simple pulse oximeters were used to diagnose infectious diseases early. Oxygen level and heart rate can be used to detect virus-related infections, including asymptomatic patient infections. Screening for asymptomatic infections is difficult, which makes national prevention and control of the outbreak more difficult. In this research, we predict the asymptomatic COVID-19 patients with the help of their oxygen level and heart rate level. To build the machine learning model we use SVM, Naïve Bayes, KNN and logistic regression algorithms on the collected dataset. The model predicts the asymptomatic COVID-19 patients early. The dataset contains 105,609 cases with 16 attributes, including information of patients with COVID-19 RT-PCR test results. There are ten key features to be selected from the given dataset for the experiment. First, we analyze the features of the dataset to find the most important features. Heart rate and SPO2 are the most important features of the dataset for predicting asymptomatic COVID-19 patients. Our machine learning technique uses four ML algorithms. Through feature correlation, we improved accuracy by using ten main features. Following that, we trained and evaluated the data with 80-20% splits. This study compares the results of the model with other studies and finds that our technique achieves the best results from others. The current study's findings show that the model developed with the KNN algorithm is more effective at detecting the likelihood of the infected patients and achieved the highest 98% accuracy, 87% precision, 97% recall, 92% f1 score and making it the best model among those that have been developed with other algorithms such as support vector machine, naïve bayes and logistic regression.

Povzetek: Opisana sta razvoj in vrednotenje modelov strojnega učenja za zgodnje odkrivanje asimptomatskih bolnikov s COVID-19, pri čemer so ključni podatki o srčnem utripu in ravni kisika. Z uporabo algoritmov SVM, Naïve Bayes, KNN in logistične regresije na zbranem naboru podatkov študija ugotavlja, da model KNN dosega najvišjo točnost.

1 Introduction

Infectious pneumonia was reported in the Chinese city of Wuhan in December 2019 [1]. This infection is designated as Corona Virus Disease-19, in short form COVID-19. It has been labelled a pandemic by the World Health Organization (WHO). The disease has covered several countries globally and has contaminated millions of people worldwide, and 4.3 million people died from COVID-19. Unfortunately, COVID-19 has no effective and reliable treatment/cure. Because the nature of COVID-19 is yet unknown, it will take a longer time to produce an effective COVID-19 vaccine. On March 23, 2022, a total of 470 million COVID-19 infected cases were reported, and 6 million deaths all over the world [2]. Fever, cough, and fatigue are all symptoms that are close to the flu and must be recognized for early COVID-19 prediction. Surprisingly, a patient with no symptoms could transmit the COVID-19 virus to other people. COVID-19 affects every country in the world and there is a need to be various advancement, and new technologies are required to handle the different problems caused by the impact of issues in the health system [2]. One of the reasons COVID-19 has spread so quickly is that people infected with the virus may have no symptoms but still be contagious; they don't look or feel sick but can transmit the virus without even realizing it. Asymptomatic

transmission refers to the spread of disease without the presence of symptoms [3, 4].

An asymptomatic case is one diagnosed with disease symptoms, whereas an asymptomatic case is one with no apparent symptoms. However, you might have heard a word that confuses you: 'pre-symptomatic.' A pre-symptomatic case seems to be someone who has not had any symptoms yet. It's a little more complex than that since pre-symptomatic can also mean asymptomatic. Physical distancing, social distancing, hand sanitization, use of nose and face masks, and handwashing have all been used to avoid the spread of COVID-19 around the world. However, the poor healthcare systems, financial pressure, overcrowding, community attitudes, poverty, and the COVID-19 preparedness and response plan are the major challenges. The majority of people infected with the COVID-19 virus suffer respiratory symptoms. They begin to feel unwell, fever, cough, sore throat, or sneeze [5]. They may develop gastrointestinal symptoms in some people. Many patients have asymptomatic infections, which means they have no symptoms at all. The role of asymptomatic cases in spreading the pandemic was addressed by Maria Van Kerkhove figure 1 [6]. She made comments about the uncertainty by defining "asymptomatic cases" in a way that excluded people who were genuinely pre-symptomatic. Here's the problem. The people are known as 'asymptomatic' if they test positive for COVID-19 (confirmed case) but show no symptoms. However, if the infected person later shows symptoms, you reclassify their initial infection as 'pre-symptomatic' figure 1 represents the two types of coronavirus cases in the Venn diagram above, while the overlapping part represents various stages of infection. World Health Organization describes asymptomatic patients in a very specific system. Asymptomatic patients are only concerned that they never show symptoms (light blue portion of figure 1). World Health Organization ignores patients who move to symptomatic cases after a pre-symptomatic period in which they are active in asymptomatic transmission of the virus. Asymptomatic cases are those that have no symptoms when they spread Covid-19 (blue plus green over-lapping section).

This [7] study addresses challenges in understanding COVID-19's early spread, emphasizing non-countermeasure factors like population density and mobility. By leveraging machine learning it identifies socio-environmental determinants influencing transmission. The research highlights the difficulty of isolating these factors and the need for holistic strategies to complement traditional interventions, offering valuable insights to enhance public health planning.

The world is suffering from a pandemic disease of virus infection, and no specific or traditional treatment for this infection as of now. Studies have shown that COVID-19 caused an estimated $62 billion loss to China's economy and over $280 billion globally in the first quarter [8]. It has been on people's minds ever since the coronavirus spread. And people did a lot of psychological effects. Due to this people turned to hospitals. That is why it was necessary to develop a system that could predict asymptomatic COVID-19 patients early. Many studies conducted research on chest x-ray images and lung images for detecting or predicting COVID-19 patients. And they only focus on symptomatic patients. We didn't see many studies on the prediction of asymptomatic COVID-19 patients. Studies conducted on asymptomatic patients consider only the oxygen level of the patient. In past, most studies conducted research on COVID-19 prediction using machine learning algorithms [9-11]. These studies use labelled dataset and only symptomatic patients were considered. There is no study conducted on asymptomatic patients that should include pulse rate and oxygen level for prediction of asymptomatic patients. Asymptomatic patients do not have any common symptoms. They are dangerous as they spread the coronavirus without even knowing that they are infected, and they can also have respiratory issues and severe lung damage. For accurate prediction of an asymptomatic patient's oxygen level and pulse rate plays an important role. In this study, our aim is to add both data streams pulse rate and oxygen level to improve the reliability of the data, which will help to more precisely early detection of asymptomatic COVID-19.

Contributions of this research are as follows:

1. In this research we develop a machine learning technique using two new features (oxygen level and pulse rate) for accurate prediction of asymptomatic COVID-19 patients
2. An early prediction of asymptomatic patients using machine learning techniques reduces the massive load on the healthcare sector all over the world.
3. The performance of the machine learning model is analyzed by comprehensive experiments with a baseline and two main proposed features.

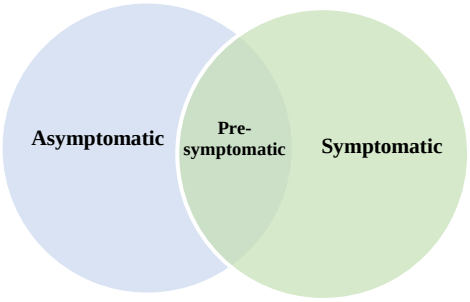


Figure 1: Differentiation of asymptomatic, pre-symptomatic and symptomatic

COVID-19 has become most hot topic of current research. We find a lot of research about COVID-19 to find the solution for early detection of viral disease. A brief overview of related studies about COVID-19 is presented in section 2, section 3 presents the methodology of asymptomatic COVID-19 prediction, section 4 presents the results and validation, section 5 presents the comparative study with the existing study and section 6 presents the conclusion and future work.

2 Related work

For predicting and analyzing the COVID-19 patients [9] study used different machine learning regression techniques. The study used a dataset that is available in

Kaggle for predicting and analyzing the patients. The author used polynomial and linear regression models for the prediction of future confirmed cases. The aim of this study [10] was prediction of infected patients of COVID-19 using ML techniques. From March 17 to March 30, 2020, data was collected through 235 patients at the Hospital of Brazil, of which 102 had 43% positive COVID-19 diagnosis from RT-PCR testing. 70% of the patient's dataset was randomly selected and used to predict diseases with different machine-learning techniques. Their performance was tested on 30% of the dataset. The support vector machines method produced the best predicting result AUC 85%, Sensitivity 68%, Specificity 85%. COVID-19 is an infectious disease that infects billions of people over the world. In this paper [12] authors proposed a forecasting model using LSTM, Bi-LSTM and SVR. The Bi-LSTM provides the best and better results for the prediction of COVID-19 and also better management and planning. COVID-19 affects people in the age categories of 20-30, 30- 40, and 40-50, according to the experiments [13]. The correlation matrices are used to figure out how the attributes of the datasets are related. The importance of the attributes is calculated for the machine learning classifiers that are developed. In which Random Forest Classifier gives higher performance than other machine learning models.

Utilizing the epidemiology labelled dataset [14] of COVID-19 patients, for detection of COVID-19 different ML techniques were used. The training dataset was used to train the models for 80% of the data, and the test dataset was used for the remaining 20%. Performance evaluation of the model, the machine learning decision tree algorithm achieved the best accuracy of 94% according to the results. This study used ML model for predicting the COVID-19 patient's invasive mechanical ventilation within 24 hours of their initial stage for evaluation of the performance of the model [15]. Five US hospitalized infected COVID-19 patients' dataset were used in this research. A total of 197 infected patients' data were used for the forecasting using machine learning techniques. The method had a much higher sensitivity 90% than the previous algorithm which had a sensitivity of 78%, while also having a significantly higher specificity ($p<0.05$). Machine learning algorithms are used in this study [16], and two different solutions are discussed: one is for calculating the likelihood of becoming COVID-19 infected patient, and the other one is forecasting the COVID-19 positive cases. Different algorithms were tested, and the one that produced the most accurate results was chosen.

In this study [17], a prediction approach depends on patient characteristics tracked while quarantine duration at home was used for the prediction and outcome of COVID-19 patients. 287 COVID-19 samples from patients at Saudi Arabia's King Fahad University Hospital were used in the study. Three classification techniques were used to examine the data. For data partitioning, 10-k cross-validation was used, and SMOTE was used to correct the data imbalance. Experiments were carried out with 20 clinical variables that were found to be relevant in predicting survival versus death in COVID-19 patients. Having an accuracy of 95%, the conclusion of the study showed that random forest performs better than other classifiers. An online questionnaire was created as a data collection for this investigation [18]. This information was fed into a different machine learning prediction. Based on their indications and symptoms, these models were used to predict prospective COVID-19 patients. In comparison to the other models, the MLP has achieved an accuracy of 91% among the top accuracy percentage. The AdaBoost method is used to enhance a fine-tuned Random Forest model in this work [19]. In this study author used geographic, demographic, health and travel data for infected patients of COVID-19. For predicting the COVID-19 patients using a dataset from South Korea, data mining models were designed [20]. This study helps to predict the likelihood of recovery from disease or death and severe cases of illness. The dataset contains males and females both genders and the majority have ages between 20 to 70 years. By applying data mining techniques, the model achieved 94% accuracy and 86% F1-socre. Using the programming language, different machine learning classification algorithms were applied directly to the dataset to generate the models. The results of the current study show that a model built using the decision tree machine learning technique is more effective at predicting the COVID-19 with a 99% accuracy.

Because predicting cardiac disease is a difficult task, it is necessary to automate the process to avoid the risks connected with it and to inform the patient well in advance. This paper [21] makes use of the UCI machine learning repository's heart disease dataset. In this study author classifies the risk level of the patients and predicts heart disease likelihood. The results of the model show the random forest achieved the highest accuracy of 90% than other ML algorithms. In the healthcare industry, data mining techniques are typical for predicting and analyzing a large amount of dataset. The model is based on supervised ML methods and present numerous attributes associated with heart disease. The author used UCI based dataset for the prediction of infectious disease from the database of Cleveland of heart disease patients [22]. There are 303 instances and 76 attributes in the collection. Only 14 of the 76 attributes are tested, despite their importance in proving the efficacy of different algorithms. The basic reason for this study is to predict the likelihood of patients having cardiac disease. The results show that K-nearest neighbor achieves the highest accuracy score.

Table 1: Critical evaluation table

Ref	**Dataset (Size & Source)**	**ML Technique**	**Best Metric**	**Key Strength**	**Key Weakness**
[9]	Kaggle (COVID-19)	Polynomial, Linear Reg.	AUC: 85%	Simple models, public data	Moderate sensitivity
[10]	Brazil hospital (235 patients)	SVM	AUC: 85%	Real-world data	Small dataset
[12]	Not specified	LSTM, Bi-LSTM	Best: Bi-LSTM	Strong temporal prediction	Lacks dataset & metrics details
[13]	COVID-19, demogra	Random Forest	High performance	Attribute importanc	Metrics vague

	phic focus		(unspecified)	e analyzed	
[14]	Epidemiology dataset	Decision Tree	Accuracy: 94%	High accuracy	Feature engineering not detailed
[15]	US hospitals (197 patients)	Various ML algorithms	Sensitivity: 90%	Improved sensitivity	Small dataset
[16]	Epidemiological dataset	ML algorithms	Not detailed	Dual-purpose prediction	Ambiguous reporting
[17]	Saudi Arabia (287 patients)	Random Forest, SMOTE	Accuracy: 95%	Balanced data, robust validation	Small dataset
[18]	Online questionnaire	MLP	Accuracy: 91%	Innovative data collection	Limited demographic clarity
[19]	South Korea demographic dataset	Random Forest, AdaBoost	Accuracy: 94%, F1: 86%	Effective AdaBoost enhancement	Limited generalizability
[20]	South Korea (20–70 years, gender mix)	Decision Tree	Accuracy: 99%	Exceptional accuracy	Overfitting risk
[21]	UCI Heart Disease (303 patients)	Random Forest	Accuracy: 90%	Effective cardiac risk prediction	No imbalance handling
[22]	Cleveland Heart Dataset (303 patients)	KNN	Best for dataset	Simplicity	No full metrics reported

Table 1 shows the studies using machine learning for COVID-19 and heart disease prediction, leveraging datasets like Kaggle, UCI, and hospital datasets. ML techniques such as Random Forest, SVM, and LSTM achieved accuracies up to 99%, but limitations included small datasets and unclear metric details in some cases of the literature.

According to the research that has been done so far, diagnosis and prediction of the COVID-19 pandemic with ML techniques have played an important role, which can be used help to ease the burden on healthcare systems. There is no work has been published in Pakistan that uses labelled datasets of COVID-19 asymptomatic cases to create supervised ML techniques for the prediction of COVID-19 patients. Also, there is no work has been published on asymptomatic COVID-19 patients using two main data streams heart rate and oxygen level of the patients. As a result, the purpose of this study is to look into these gaps.

3 Method

In this study, the process for developing a ML method for the prediction of infected COVID-19 patients using a labelled dataset is illustrated in Figure 2.

3.1. Dataset

A dataset of about 0.1 million COVID-19 suspected cases from the Hospital located in Pakistan, is used for this study. The dataset includes various types of details like age, gender, blood pressure, cholesterol, pulse rate, and oxygen level for each patient's situation. Our work focuses on the patient's heart rate and oxygen level. The results of COVID-19 cases in Pakistan are included in the dataset. The dataset contains 105,609 cases with 16 attributes, including information of patients with COVID-19 RT-PCR test results.

3.2. Data processing and analysis

This is the very first step in the diagnostic procedure. It consists of three steps: handling null values, data redundancy removal, and selection of important features. After testing the whole patient's age group, cholesterol, and blood pressure, the missing value of a particular attribute is substituted. If the majority of a patient's attribute values match, the value is substituted in the same place. By removing redundant (irrelevant) attributes, redundancy removal reduces the size of the data. By mapping the heat map and checking the association between the features, the significant features for analyzing the suspected asymptomatic COVID-19 patients are chosen. After the original dataset is prepared, only important features are extracted, and null values are removed.

There are 0.1 million instances in the extracted dataset with ten attributes including city, age, sex, heart rate and spo2 (oxygen level), bp_systolic_mmHg, bp_diasystolic_mmHg, cholesterol, glucose and smoke. We consider only two cities of the dataset Islamabad and Rawalpindi in Pakistan. The City and Sex attributes have object datatype and Age, Heart Rate and SpO2 have integer datatype. Table 2 shows some sample instances of the extracted dataset. The city instance has 2 cities located in Pakistan Islamabad and Rawalpindi. The dataset is taken from these two cities to use in this study. Age instances have different numbers of ages. Heat Rate shows whether a patient has a high heart rate and SpO2 shows the patient's oxygen level.

There are no missing values in the extracted dataset. Figure 3 shows the gender frequency in the dataset. In this study males and females both included in experiments. There are 68654 male patients and 36954 female patients in the dataset. Figure 4 shows the original dataset before normalize and after normalize the dataset.

Table 2: Sample of dataset

Sr. No	Attribute	Datatype
1	City	Object
2	Age	Int
3	Sex	Object
4	Heartrate	Int
5	SpO2	Int
6	bp_systolic_mmHg	Int
7	bp_diastolic_mmHg	Int
8	Cholesterol	Int
9	Glucose	Int
10	Smoke	Int

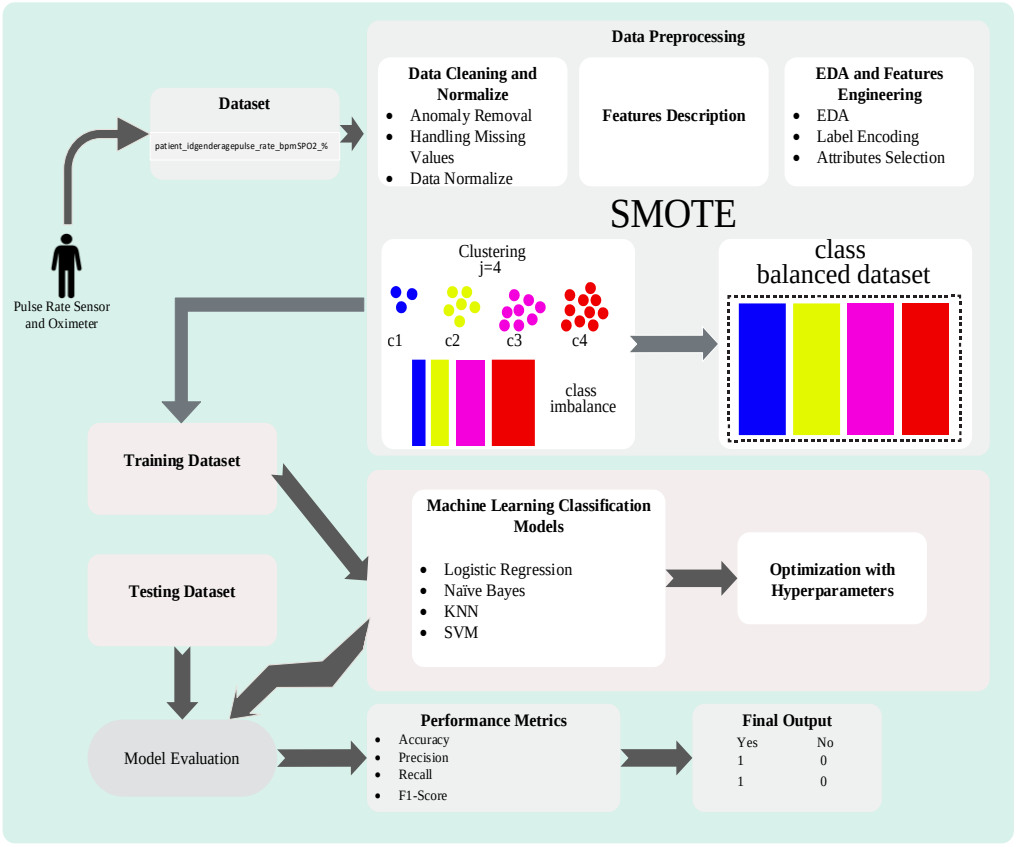


Figure 2: Proposed framework for prediction of asymptomatic COVID-19 Patients

We have used minmax scaling to normalize the dataset. In minmax scaling every value in the column with a new value using the following formula.

$$m = \frac{X - Xmin}{Xmax - Xmin}$$

To normalize the data, we use the normalize function. It takes an array as input and converts the values to a range between 0 and 1. The output array has the same dimensions as the input array. Normalized data helps to convert the numeric column values in the dataset to a standard scale while keeping variations in ranges of values in the dataset. We need to normalize the data because dataset have different ranges of features.

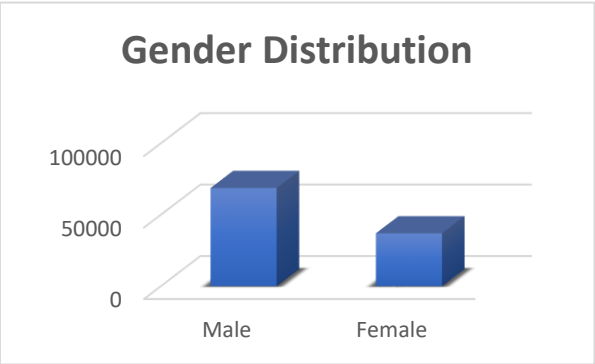


Figure 3: Gender distribution in the dataset

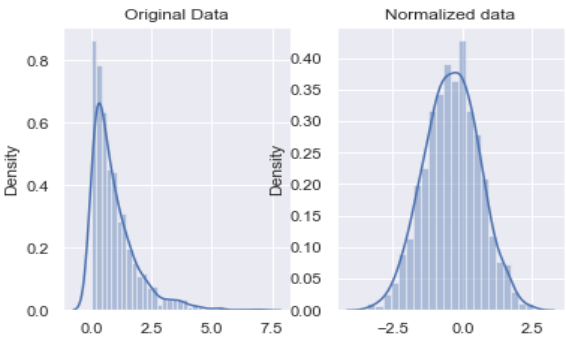


Figure 4: Before normalize and after normalize the dataset

3.3. Handling imbalanced data

Data imbalance is one of the most difficult problems to solve in data analysis, and it frequently leads to overfitting the model. The dataset to be used in this thesis is also unbalanced, as shown in Figure 5. The total number of entries in the suspected category is 13864, whereas the total number of records in the good health category is 91744.

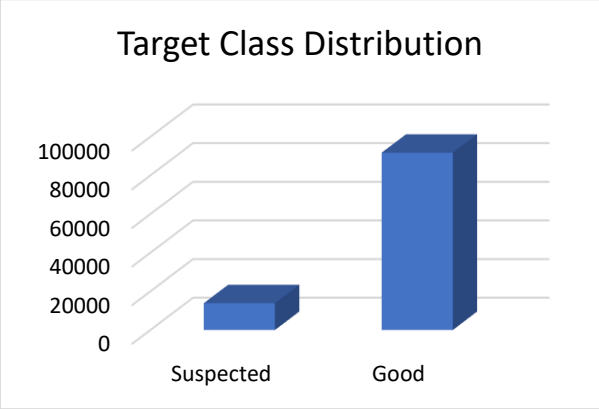


Figure 5: Target class distribution of the dataset

To address the data imbalance, a synthetic minority oversampling technique (SMOTE) based on K-nearest neighbor (KNN) was applied. SMOTE is a machine learning technique created by [23] to overcome the problem of imbalanced datasets. First, we divided the COVID-19 data into two parts: 80% training data and 20% test data. The training dataset was then oversampled using SMOTE, and the oversampled data was utilized to train machine learning models. We calculated the cross-validation score and the test score on the test dataset. The k-nearest neighbor (KNN) technique is utilized in the SMOTE algorithm to determine the Euclidean distance between minority class instances in order to create new class labels in the neighborhood. Using SMOTE the minority class set B, the k-nearest neighbors of x are calculated by computing the Euclidean distance between x and each other sample in set B for each x € B. The unbalanced proportion sets the sampling rate S. S samples (s1, s2,...sn) are randomly selected from their k-nearest neighbors for each x € B, and they form the set B1. The following formula is used to generate a new example for each xk € B1 (k=1, 2, 3...n): x' = x + rand(0, 1) * |x - xk|, where rand(0, 1) denotes a random number among 0 and 1 and xk denotes Euclidean distance with neighbors. Jupyter Notebook and the sklearn library were used to implement the models in Python. The data was partitioned using a 10-fold cross-validation technique.

3.4. Machine learning classifiers

This research used the preprocessed data to build a predictive model for our prediction framework. The aim of this model is to predict how likely a patient is to become infected with COVID-19. We trained the model on dataset which we collected form the hospital. Classification algorithms are used to determine if the patient has a high risk of COVID-19 infection. The prediction can be done using different classification algorithms. KNN, Naïve Bayes, SVM, and Logistic Regression are selected for COVID-19 prediction due to their complementary strengths. KNN classifies patients by similarity, Naïve Bayes handles probabilistic reasoning, SVM excels in high-dimensional spaces and Logistic Regression offers interpretable binary classification. Together, they ensure accurate and efficient identification of high-risk patients.

3.4.1. Naïve Bayes (NB)

In the Naive Bayes algorithm, the predictor values on a particular class are independent of other values of predictors. For the classification of learning tasks in which features of the COVID-19 dataset are differentiated based on a specified instance, the machine learning NB algorithm is used [24]. Class conditional independence is the term for this assumption. For classification assignment, NB is a Bayes theorem-based probabilistic classifier [25]. The Bayes theorem is as follows:

$$P\ (A|B) = \frac{P\ (B|A)\ P\ (A)}{P(B)}$$

Input:

Dataset of Training T,

T= (t1, t2, t3, .. , tn) : in the testing dataset, the value of the predictor variable.

Output:

Evaluate with test data.

Step:

1. Look at T, the training dataset.
2. Determine of calculate the mean and standard deviation of the predictor variables for each class.
3. Repeat again and again
   Calculate the likelihood of zi in each class.
   Until all predictor variables' probabilities (t1, t2, t3,..., tn) have been calculated.
4. For each class, calculate the prediction with the help of bayes theorem.

Get the most accurate prediction

3.4.2. Support vector machine (SVM)

A supervised learning approach [26] that is based on ML algorithm that can be helpful in handling regression and classification problems. In order to do a classification task in SVM, it is necessary to test and train data that contains some features of the dataset. Because each feature in the dataset includes more than one target value, the basic objective of SVM is to develop a model that can predict the target values in the dataset.

Following is the procedure for applying SVM

Input Data

d* variables and a binary result are included in this data set..

Output

Variables are ranked in order of their relevance.

Find the best values for the SVM model's tuning parameters; then the SVM model will work properly

d ← d*

while d ≥ 2 **do**

SM M_d ← SVM using the d variables optimal tuning parameters and in the data observations

w_p ← calculate the vector's weight of the SM M,, (w,,1, ... , w,,,,)

criteria for ranking ← (w_{d1}^2 , ... , w_{dd}^2)

criteria for minimum rank ← In the rank criterion, the variable with the lowest value vector

Data that have minimum rank requirements should be removed.

$Rank_p \leftarrow$ criteria for minimum rank

$D \leftarrow d - 1$

end

$Rank_1 \leftarrow$ a data variable $\notin (Rank_2, \ldots, Rank_{d^*})$

return $(Rank_1, \ldots, Rank_{d^*})$

3.4.3. K nearest neighbor (KNN)

KNN is a simple ML algorithm, which is very helpful to apply on both regression and classification tasks [27]. The KNN algorithm uses a similarity measure to store and classify new data. A distance function in KNN indicates how new data in the dataset is grouped into related classes by a majority vote of its neighbors. The distance between training and testing data is calculated using Euclidean distance.

Input

A n * n distance matrix D(1 ….. n,1….n) and an index s of the starting point.

Output

calculate the distance and predict the results.

Set the value of K

(Estimating the nearest neighbor)

for n = 1 to d

calculating the distance from x to j_i

if <= k

then add j_i to E

else if j_i is closer to x than any preceding nearest neighbor

after that, delete the outermost neighbor and contain j_i in the set E

3.4.4. Logistic regression (LR)

LR is a supervised ML algorithm. It performs a regression function. Its main applications include forecasting and finding relationships between variables. Logistic Regression is a machine learning algorithm for predicting the outcome of classification learning tasks. This algorithm is utilized to define the relationship between categorical dependent features and independent features [28, 29]. When dependent features of the datasets have binary values, this algorithm can be used [30]. The dependent variable (y) value is estimated using logistic regression based on the independent variable (x) value. As a result of this technique, a relationship between x (input) and y (output) is detected (output).

$$P = \frac{e^{a+bx}}{1 + e^{a+bx}}$$

Input

Training data

1. For i ← 1 to k
2. For each training data instance d_i
3. Set the target value for the regression to

$$z_i \leftarrow \frac{y_i - P(1 \mid d_j)}{\left[P(1 \mid d_j) * (1 - P(1 \mid d_j))\right]}$$

4. Initialize the weight of instance d_j to P $(1 \mid d_j) * (1 - P(1 \mid d_j)$
5. finalize a (f_j) to the data with class value (z_j) & weights (w_j)

Classification label decision

Assign (label class:1) if P $(1 \mid d_j) > 0.5$, otherwise (label class: 2).

3.5. Training and testing

We performed our experiment using an 80% training dataset and a 20% testing dataset for each of the four machine-learning algorithms. The accuracy of different machine learning algorithms in predicting COVID-19 asymptomatic patients is shown in Figure 6. Furthermore, as shown in figure 6, the KNN provides the highest level of accuracy, i.e. 98% accuracy. Logistic Regression performs the lowest in terms of accuracy, with a score of 92%.

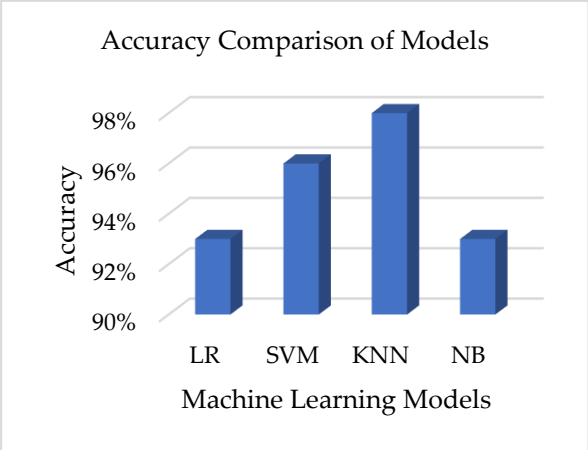


Figure 6: Accuracy comparison of four machine learning algorithms

Figure 7 shows the confusion matrix of four machine learning algorithms using a training dataset of 80% and a testing dataset of 20%.

True positive (TP)

The number of positive cases that have been labelled and are still positive.

False positive (FP)

The number of instances that were labelled as positive but were actually negative using the predictive model.

False negative (FN)

This is the number of instances that were labelled as negative by the predictive model but are actually positive.

True negative (TN)

This is the number of instances that have been labelled as negative yet are actually negative.

True Positive indicates that the percentage of patients known in the database as COVID-19 affects patients and is the best predicted of all the dividers. However, a False Negative class was created for COVID-19

	Positive (1)	Negative (0)
Positive (1)	2311 (TP)	472 (FN)
Negative (0)	1051 (FP)	17288 (TN)

(a)

	Positive (1)	Negative (0)
Positive (1)	2344 (TP)	439 (FN)
Negative (0)	389 (FP)	17950 (TN)

(b)

	Positive (1)	Negative (0)
Positive (1)	2534 (TP)	249 (FN)
Negative (0)	977 (FP)	17362 (TN)

(c)

	Positive (1)	Negative (0)
Positive (1)	2304 (TP)	479 (FN)
Negative (0)	930 (FP)	17409 (TN)

(d)

Figure 7: Confusion matrices. (a) Naïve Bayes. (b) SVM. (c) KNN. (d) Logistic regression

with affected patients, but because it was predicted wrongly, they were unable to be attacked. In the same way, the True Negative class category correctly predicted all of the patients who were not attacked. Also, the False Positive category is incorrectly reported.

4 Results and validation

While prediction of asymptomatic infected patients of COVID-19, early prediction of infected patients helps to minimize the huge load on the health-care system.

Table *2*: Summary of results

Models	Accu	Precision	Recall	F1-Score
NB	93%	%71	%82	76%
SVM	96%	86%	84%	85%
KNN	98%	%87	97%	92%
LR	93%	%69	%83	75%

Using a dataset that is collected from a hospital in Pakistan, logistic regression, SVM, Naïve Bayes and KNN model for the prediction of asymptomatic COVID-19 patients were used. Accuracy, precision, recall, and F1-score parameters were used for the assessment of the efficiency of all machine learning models. Table 2 shows the machine learning model performance results.

We validate the results of our training model by testing unseen dataset. The training-set accuracy score of using KNN is 0.9606 while the test-set accuracy to be

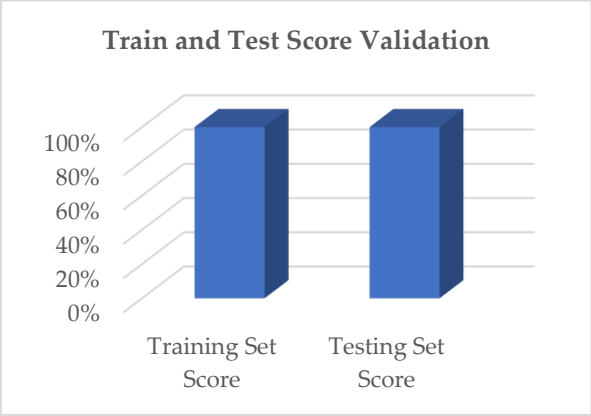


Figure 8: Train and test score validation

0.9420. These values are quite comparable. So, there is no question of overfitting the model. Figure 8 shows the train and test scores.

4.1. K-Fold Cross-validation

When using cross-validation, the dataset is randomly divided into 'k' groups. One group serves as the test set, while the others serve as the training set. On the training set, the model is trained, and on the test set, it is scored. The method is then repeated until each distinct group has been employed as a test set. In this paper, we used 10-fold cross-validation, which divides the dataset into 10 groups and trains and tests the model 10 times, giving each group a chance to be the test set.

The 'holdout' method is the same as the train-test-split method we used earlier. Because the holdout method's score is dependent on how the data is split into train and test sets, cross-validation is preferable to it. Cross-validation allows us to test the model on multiple splits in order to obtain a better understanding of how it will perform on unknown data. The results of cross-validation and test scores are shown in figure 9.

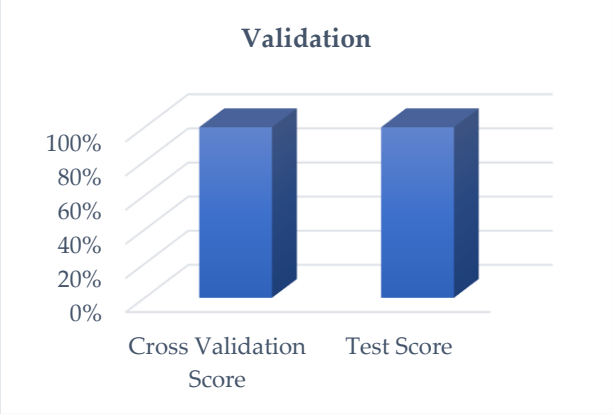


Figure 9: Comparison of 10-fold cross-validation and test score

We'll use the 'cross-val score' function with a cross-validation value of 10 to train and test our model using cross-validation. Our k-NN model and data are passed as arguments to the 'cross-val score.' Then it divides our data into ten groups and fits and scores it ten times, each time saving the accuracy score in an array. The accuracy scores will be saved in the 'cross_val_score' variable.

Our mean cross-validation score is around 89.6%. This is a more accurate portrayal of how our model will perform on unseen data than the holdout method we used previously.

5 Comparative study of our with the existing methods

The performance of machine learning classifiers is evaluated using three based papers as well as our proposed technique using new features and with the results being critically evaluated. The accuracy of the proposed technique experiment was used to evaluate their performance. The goal of this experiment is to look at how proposed new features interact with based-paper techniques for early prediction of COVID-19 patients. These are the paper [13, 14, 18, 31] considered for comparison with our machine learning technique. The comparison of machine learning technique results is shown in table 3. With the comparison of three base papers, our proposed

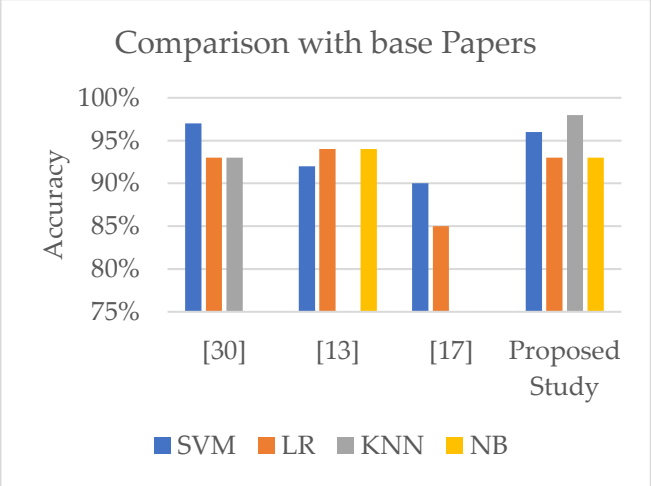


Figure 10: Accuracy comparison of proposed research

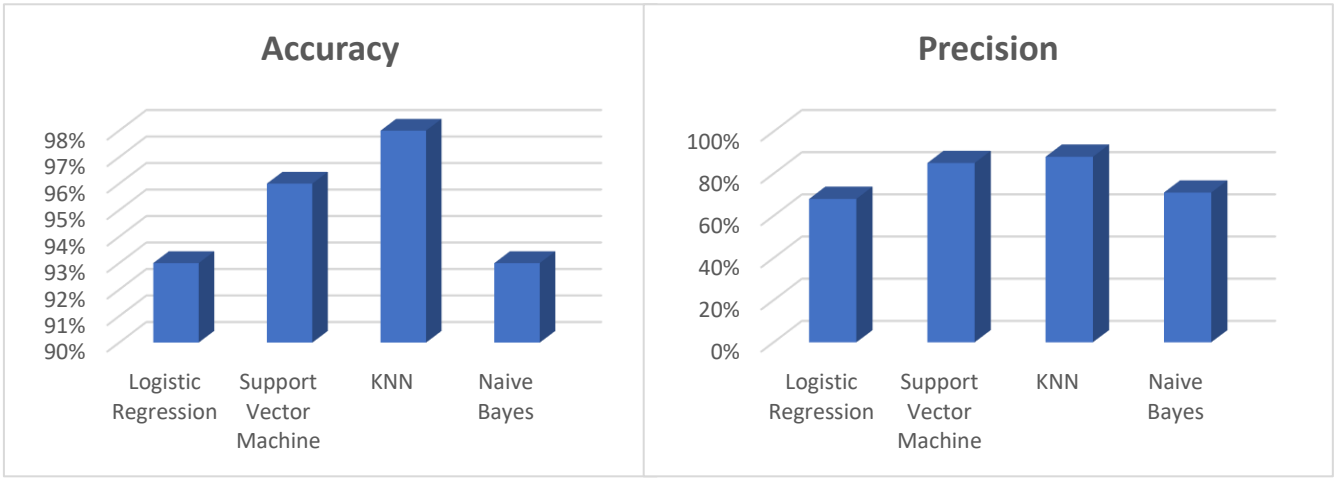
research achieved the best results with the use of KNN algorithm on the accuracy performance measure

In figure 10 we have compared accuracy with based papers and achieved the highest accuracy 98% of the model.

Table 3: Comparison of proposed research with based papers

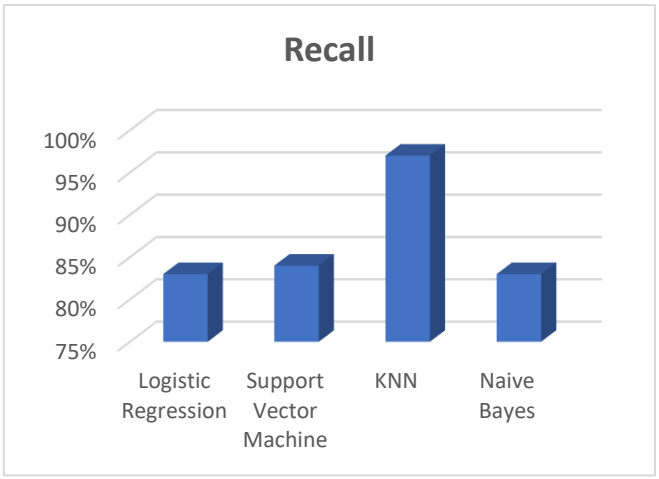
Based and Proposed Methods	SVM	LR	KNN	NB
A. F. de Moraes Batista [31]	97%	93%	93%	
L. Muhammad, E. A. Algehyne [14]	92%	94%		94%
E. Fayyoumi, S. Idwan [18]	90%	85%		
Proposed Study	96%	93%	98%	93%

The work of this research presents the early prediction of asymptomatic COVID-19 patients. There are four ML algorithms including support vector machine, logistic regression, KNN and naïve bayes used in this research. With the comparative analysis our proposed technique for the prediction of asymptomatic COVID-19 patients using main features of the dataset like heart rate and spo2 and achieved the best accuracy of 98% (Table 3). The protocol of COVID-19 asymptomatic patients such as heart rate and spo2 are the most important features for the prediction of patients. The best performance based on accuracy KNN perform well and achieves best accuracy. Figure 11 shows the results of our model in graphical representation, in graph KNN performs better than other machine learning algorithms.

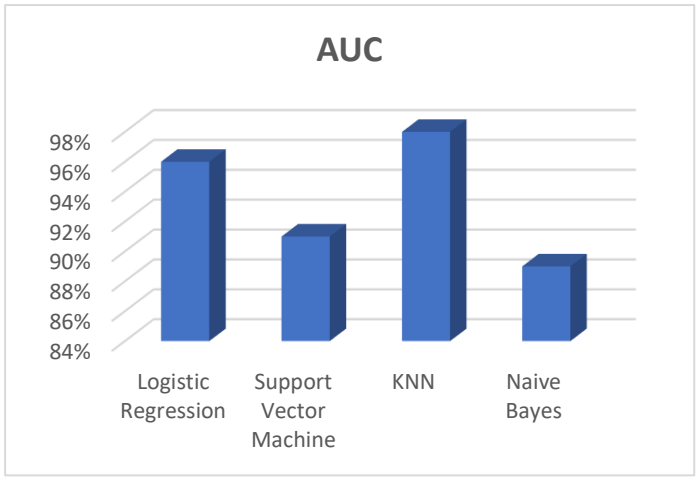


(a)

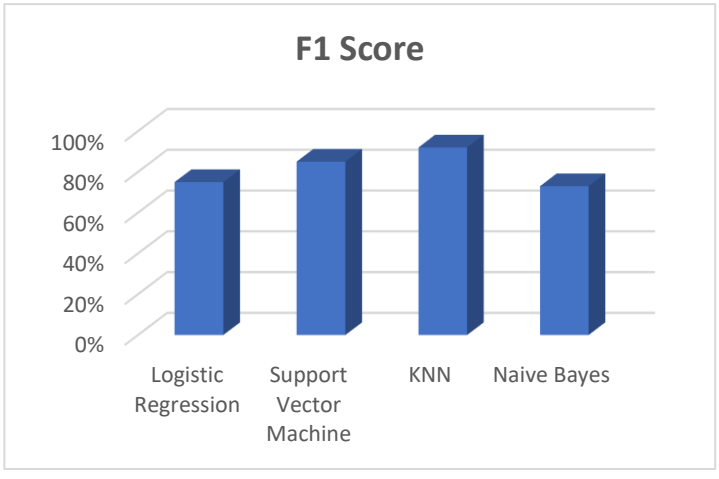
(b)



(c)



(d)



(e)

Figure 11: Performance measures of four machine learning algorithms (a) Accuracy (b) Precision (c) Recall (d) AUC (e) F1 Score

6 Conclusion and future work

The COVID-19 pandemic, like other infectious diseases such as tuberculosis, HIV/AIDS, hepatitis, and measles now appears to be endemic. It has infected over 223 countries and territories throughout the world, as well as this disease infects people all around the world. This disease spreads through sneezing and coughing after close contact with an infected patient. No medically approved vaccination or therapy is available yet for COVID-19. A symptomatic case is one diagnosed with disease symptoms, whereas an asymptomatic case is one with no apparent symptoms. Developing the machine learning system in the medical healthcare system provides effective emergency services to patients. E-health application is also used in the different medical fields, i.e. early detection and monitoring of medical issues and emergency notification.

As an alternative approach, COVID-19 pandemic cases are being diagnosed using supervised ML algorithms. The use of ML algorithms for COVID-19 prediction in patients reduces the load of work on sufficient healthcare sources across the world. With the help of machine learning models, we are able to early predict asymptomatic COVID-19 patients. The models of machine learning were trained using 80% of the dataset and then tested dataset with 20%. In terms of accuracy, the KNN model was the best of all the models developed, with a score of 98%. In terms of accuracy, precision, and recall the KNN model shows top results among all models, with 98%, 88% and 97%, respectively.

We have a small amount of data, but with the help of a significant amount of data, the same mechanism can be used with more deep-learning models for better results. In the proposed research, there are two main variables used for the asymptomatic COVID-19 patients but as the data is increasing due to new variants of the virus, in the future more variables like lungs and heart damage can be added for better predictions.

7 Declarations

Ethics approval and consent to participate

The dataset used in this study was provided by a government hospital (PIMS) to our university under a formal Memorandum of Understanding. The dataset was anonymized and all patient-identifying information was removed prior to access by the research team.

In Pakistan, there are currently no specific regulations governing the use of human data in research. However, to ensure strict compliance with ethical standards and to safeguard patient privacy, the hospital shares such data exclusively with universities under formal agreements. These agreements ensure that the data is used responsibly and ethically. Universities, in turn, provide access to students under strict supervision and after ensuring full observance of professional conduct, thereby minimizing the risk of misuse.

Given that the dataset was anonymized and shared under these regulated conditions, specific ethical approval from an Institutional Review Board was not required. The study adhered to the principles of the Declaration of Helsinki, institutional guidelines and the provisions of the data-sharing agreement between the hospital and the university.

Availability of data and material

The datasets generated and analyzed during the current study are not publicly available but available in the manuscript due to privacy restrictions but are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

Hafiz Haseeb Tasleem played a key role in outlining the research methodology and identifying the research problem through an extensive review of the literature. Mueed Ahmed significantly contributed by designing and conducting the experiments and analyzing the results. Muhammad Waqar Arshad provided detailed explanations and insights into the experiments conducted by Mueed Ahmed. Hamza Ansari constructed the abstract and conclusions, synthesizing the research findings effectively. All authors read and approved the final manuscript.

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Efficient Computing System for Satellite Image Processing Processor

A. Azhagu Jaisudhan Pazhani
Department of ECE, Ramco Institute of Technology, Rajapalayam, India
E-mail: alagujaisudhan@gmail.com

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Approximate computing plays a significant role in signal processing and image processing applications. Radix-8 approximate novel booth multiplier (R8ANBM) based on approximate novel booth encoder (ANBE) is proposed in this paper to validate approximate computing. The proposed design is synthesized and simulated in Xilinx ISE 13.2. The experimental results show that the proposed multiplier performs better in terms area, speed and energy consumption. The proposed R8ANBE reduced the number of 4 input LUTs by 23.07%, 17.94%, 19.87%, 16.66%, 13.46%, 8.33%, 12.82%, 9.61%, 12.17% and number of occupied slices by 22.33%, 30.09%, 25.24%, 29.12%, 14.56%, 17.47%, 13.59%, 12.62%, 17.47% when compared with the existing techniques such as conventional booth multiplier, R4ABM1, RAD64, ABM1, HLR-BM1, HLR-BM2, R8ABM1, R8ABM2, R8ABM3 respectively. It achieved the accuracy as 67.3% which is higher than exisitng approximate booth multipliers. The proposed R8ANBM is applied to image sharpening applications and the performances are analyzed in terms of error metrics such as ralative mean error distance, normalized mean error distance and peak signal to noise ratio. The above proposed system was implemented using 45nanometer technology library. With applications in low-power CMOS design, quantum computing, optical information processing, DNA computing, bioinformatics, and nanotechnology, there is an increasing interest in power minimization.

Povzetek: Predstavljena je izboljšana pomnilniško učinkovita porazdeljena arhitektura za 2D diskretno valčno transformacijo (DWT), prilagojeno satelitskim slikam. Z uporabo stiskanja iskalne tabele (LUT) predlagana zasnova zmanjšuje pomnilniške zahteve, hkrati pa ohranja računsko učinkovitost, kar predstavlja pomemben prispevek k visoko zmogljivim VLSI implementacijam za obdelavo slik.

1 Introduction

In this modern world, one of the recent trends in VLSI design is approximate computing which focused the tradeoff factors area, power consumption and speed. In this emerging computing method, the internal structure of the architecture is modified by eliminating certain logic gates which leads to the erroneous output for some cases. But this error is acceptable in image processing applications, data mining, filtering, digital signal processing, machine learning, computer vision, etc [1]. Due to the advantages of approximate computing [2], the researchers concentrate on different approximation approaches and utilize these approaches in certain applications. In addition to that, approximate computing plays a significant role in hardware accelerators for customization of the hardware modules and for processing large amount of data [3].

Approximate accelerators are designed in [4] by collecting the most appropriate approximate elements from libraries where lot of approximate arithmetic circuits are stored. It uses space exploration methodology for approximate circuit collection and uses machine learning techniques for estimation of computational modules. The fundamental components involved in the approximate accelerator are approximate adder and approximate multiplier. So these should be designed with low power consumption and high performance to make it well suited for effective applications. Approximate computing is also applicable for biometric security systems [5]. In this method, the runtime of the application is reduced by applying the encoding techniques to the resultant obtained from iris scanning.

Multiplier is a power-hungry arithmetic circuit used in most of the signal processing applications. To reduce the power consumption of the multiplier designs, approximate multipliers are focused by the researchers [6]. In approximate multiplication, the approximation is inserted in partial product formation or partial product reduction or partial product summation. Most of the approximation approaches uses encoding process for the partial products to reduce the complexity of the design. Then the encoded partial products are compressed with the help of approximate half adder and approximate full adder [7].

This paper proposed an approximate novel booth encoder (ANBE) for radix-8 booth multiplication. The proposed encoder reduces the number of partial products leads to the reduction in the complexity. It uses approximate half adders to generate the 3X product term thereby it facilitates the simplest method to partial product formation. The proposed radix-8 booth multiplier using ANBE is designed in Xilinx ISE 13.2 and coded in

Verilog HDL. The proposed radix-8 approximate novel booth multiplier (R8ANBM) outperforms better than existing radix-8 booth multipliers. At long last, the fruitfulness of the proposed radix-8 booth multiplier design is demonstrated with image sharpening applications.

The remaining section of this research work is as follows. Section 2 describes the works related with booth encoders and approximate multipliers. Section 3 presents the proposed approximate novel booth encoder. It also explains the logical diagram and operation of the ANBE. Section 4 explains the proposed radix-8 approximate booth multiplier and Image sharpening using proposed booth multiplier. Performance analysis is given in Section 5 and error analysis is given in Section 6. Finally, the work is concluded in Section 7.

2 Related work

Multipliers have significant importance in image processing and signal processing applications. Honglan Jiang presented an approximate radix-8 booth multiplier based on encoding methods which is used for reducing the partial product count [8]. This approximate multiplier eliminates the complexity of conventional radix-8 booth multiplier by the exploitation approximate adder which computes the sum of 1X and 2X products. This multiplier is applied in the filtering applications to evaluate the performance of the approximate radix-8 booth multiplier. The observation results showed that, there is a tradeoff between power consumption and accuracy.

Area and power efficient booth multiplier are designed in [9]. The adder and subtractor used in this multiplier are designed using multiplexers. The code block also fully designed by multiplexers. In this booth multiplier, there are no components other than multiplexers and it is well suited for graphics applications. V. Leon et al presented hybrid radix encoding techniques for partial product formation. This hybrid approach is suitable for signed multiplier where approximate radix-4 encoding approach is used in least significant bits and accurate approach is used in most significant bits [10]. In this method the highest radix values are converted to two the power of values and it is termed as rounding. Since it achieves high energy efficiency, there is a tradeoff between energy consumption and accuracy.

8 point Fast Fourier Transform is designed using approximate radix-8 booth multiplier [11] which partially performed the operation of butterfly unit. The remaining operation of butterfly unit is performed by recoded adder and Kogge Stone adder. It utilized the approximation approaches for generating 3X product leads to low power consumption. It also uses external circuit for error detection as well as error correction leads to more area. Suganthi Venkatachalam designed three different approximate booth multipliers ABM1, ABM2 and ABM3 [12]. Here, the approximation is inserted in the booth encoding process. It reduces the logic complexity presents in the partial product formation. This design is applied in Finite Impulse Response (FIR) filter to evaluate the performance of ABM1, ABM2 and ABM3. These are performing better in terms of area and power consumption with delay overhead.

Alberto A. Del Barrio et al designed a carry save radix-8 booth multiplier [13] that reduced the number of partial product rows into half. It uses 4:2 compressors for forming partial product matrix (PPM) and Kogge Stone adder for carry propagate addition. It increased the speed with area overhead due to the utilization of parallel prefix adder. Bayadir A. Issa et al designed a fused multiply add unit using radix-8 booth multiplier. It is represented in floating point format and so the 53x53 bit mantissa product is obtained by performing booth multiplication [14]. The partial products are reduced with the aid of 4:2 carry save adder tree which increased the speed of the whole unit. Jiang et al [15, 16] compared approximate arithmetic circuits to utilize these in the accumulation stages. High accuracy fixed width booth multipliers are designed and its error metrics are analyzed in [17, 18]. Choi et al [19] designed hybrid radix truncated multiplier for mobile applications. Different booth encoding approaches, approximation techniques, booth multiplier structures are discussed [20-23] to evaluate the limitations of these approaches.

3 Proposed approximate novel booth encoder (anbe)

Let A is n-bit signed multiplicand and B is n-bit signed multiplier and these are expressed in two's complement format.

$$A = -a_{n-1}2^{n-1} + \sum_{p=0}^{n-2} a_p 2^p \quad (1)$$

$$B = -b_{n-1}2^{n-1} + \sum_{p=0}^{n-2} b_p 2^p \quad (2)$$

The product can be obtained by applying novel booth encoding approach to the multiplicand B.

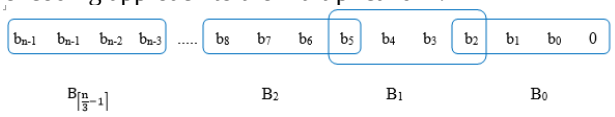


Figure 1: Grouping of multiplier bits for booth encoding

Every four bits are grouped from right to left and it is termed as a set {b_(3q+2), b_(3q+1), b_3q, b_(3q-1)}. During this group formation, the least significant bit (b_ (-1)) is assigned as zero and the most significant bit (b_(n-1)) is assigned as sign bit. Before encoding process, the multiplier bits are grouped into various sets and it is depicted in Figure 1. The encoded format for every group is represented by the following equation

$$B_q = -4b_{3q+2} + 2b_{3q+1} + b_{3q} + b_{3q-1} \quad (3)$$

In equation (1), the value of m should be lies between 0≤ q ≤(⌈n/3⌉-1). Here, the value of B_q may be 0, -1, -2, -3, -4, +1, +2, +3 or +4. Every group of

multipliers is multiplied with the multiplicand to get the partial products and it can be represented as follows.

$$Ppq=A*B_q \quad (4)$$

where Ppq represents partial products in the mth row. For every group, the most significant bit of the encoded values is considered for sign computation. If it is zero, it is termed as positive, otherwise termed as negative. During the positive cases, 2 x multiplicand (2A) can be obtained by left shifting the A by one bit and 4 x multiplicand (4A) can be obtained by left shifting the A by two bits. 3 x multiplicand (3A) can be obtained by adding A and 2A. When the sign is negative, then two's complement is applied to get the partial product row. The logic diagram of existing R8ABE1 is shown in Figure 2.

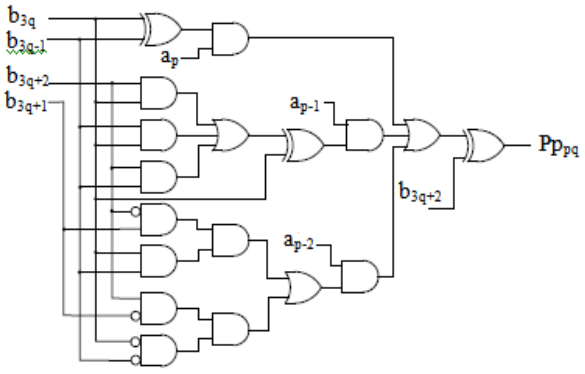


Figure 2: Logic diagram of existing R8ABE1

In R8ABE1, the partial product Pppq can be computed by the following expression.

$$Pp_{pq} = \left[a_p(b_{3q} \oplus b_{3q-1}) + a_{p-1}\left(b_{3q} \oplus (b_{3q+2}b_{3q} + b_{3q-1}b_{3q} + b_{3q+2}b_{3q-1})\right) + a_{p-2}(\bar{b}_{3q+2}b_{3q+1}b_{3q}b_{3q-1} + b_{3q+2}\bar{b}_{3q+1}\bar{b}_{3q}\bar{b}_{3q-1})\right] \oplus b_{3q+2} \quad (5)$$

The logic equation of the existing R8ABE1 is modified to reduce the area as well as power consumption of the encoder design. The logic expression given in (5) is simplified to get the novel approximate booth encoder. The partial product bit Pppq at qth row in pth position can be expressed by the following equation

$$Pp_{pq} = [a_p(b_{3q} \oplus b_{3q-1}) + (a_{p-1}(\bar{b}_{3q-1}b_{3q}\bar{b}_{3q+2} + b_{3q-1}\bar{b}_{3q}b_{3q+2}) + a_{p-2}(b_{3q-1}b_{3q}b_{3q+1}\bar{b}_{3q+2} + \bar{b}_{3q-1}\bar{b}_{3q}\bar{b}_{3q+1}b_{3q+2})] \oplus b_{3q+2} \quad (6)$$

The logic diagram of the proposed ANBE is shown in Figure 3. The proposed approximate novel booth encoder reduces the area by reducing the number of logic gates. It requires 31 logic gates to complete the encoder design which is lesser than existing R8ABE1 that requires 35 logic gates. So, 4 logic gates are reduced for every partial product row. If there is y number of partial product rows, then 4y logic gates are reduced.

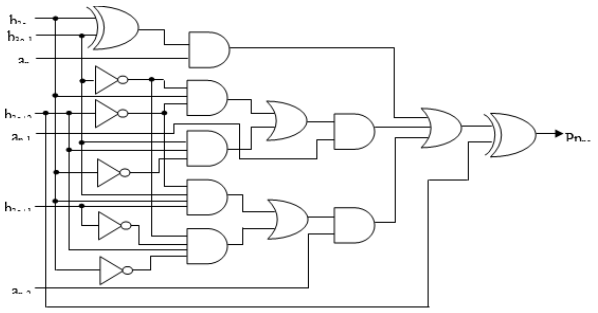


Figure 3: Logic diagram of the proposed ANBE

The truth table of the proposed ANBE is tabulated in Table 1.

Table 1: Truth table of the proposed ANBE

b_{3q+2}	b_{3q+1}	b_{3q}	b_{3q-1}	B_q	Pp_{pq}
0	0	0	0	0	0
0	0	0	1	1	a_p
0	0	1	0	1	a_p
0	0	1	1	2	a_{p-1}
0	1	0	0	2	a_{p-1}
0	1	0	1	3	$a_p + a_{p-1}$
0	1	1	0	3	$a_p + a_{p-1}$
0	1	1	1	4	a_{p-2}
1	0	0	0	-4	$\bar{a}_{p-2}$
1	0	0	1	-3	$\overline{a_p + a_{p-1}}$
1	0	1	0	-3	$\overline{a_p + a_{p-1}}$
1	0	1	1	-2	$\overline{a_{p-1}}$
1	1	0	0	-2	$\overline{a_{p-1}}$
1	1	0	1	-1	$\bar{a}_p$
1	1	1	0	-1	$\bar{a}_p$
1	1	1	1	0	0

From Table 1, it is observed that, the proposed ANBE cannot generate the exact output in 4 cases. 〖Pp〗_pq generate erroneous outputs when B_q=+3 and B_q=-3. In four cases, B_q=±3 is present; hence the probability of error is 4/16 as ¼

4 Proposed radix-8 anbe based multiplier (r8anbm)

Three major operations of multiplier are partial product generation, reduction and addition. The additional process involved in the booth multiplier is booth encoding. Since this research focused the approximate booth multiplier, approximate booth encoder is proposed. In this proposed multiplier, the partial products are generated by approximate novel booth encoding approach. The positioning of these partial products is same as the existing booth multiplier. Then the reduction of partial products is performed by 4:2 compressors, full adder and half adder. Finally, the reduced partial products are added with the area efficient and high-speed Brent Kung (BK) adder.

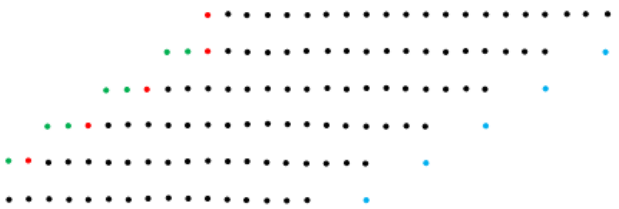


Figure 4: Dot diagram of proposed Radix-8 approximate novel booth multiplier

The dot diagram of proposed radix-8 approximate novel booth multiplier is shown in Figure 4. The blue colour, red colour and green colour denotes the sign of booth encoded digits, inverted sign bit and binary one respectively. After forming these encoded products, the partial products are accumulated using compressors and finally these are added using two operand adders.

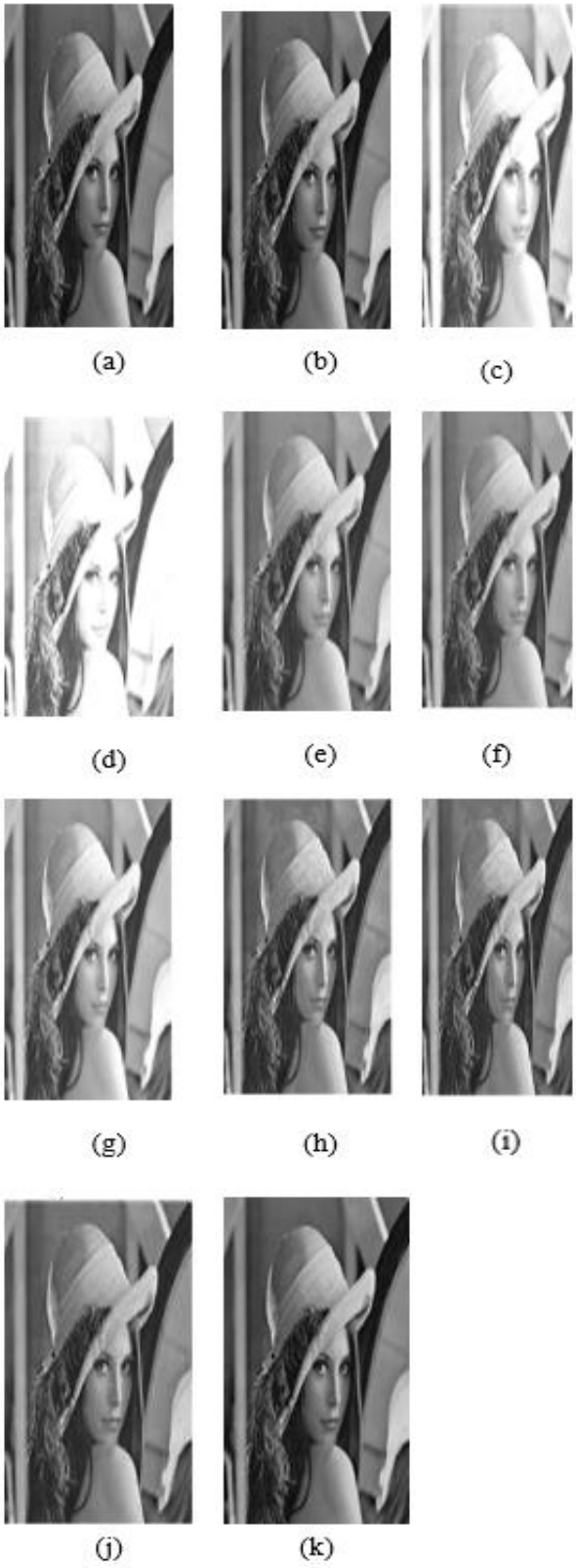


Figure 5: Image sharpening with different approximate booth multipliers: (a) Input Image, (b) Conventional booth multiplier, (c) R4ABM1, (d) RAD64, (e) ABM1, (f) HLR-BM1, (g) HLR-BM2, (h) R8ABM1, (i) R8ABM2, (j) R8ABM3, (k) Proposed R8ANBM

The 225x225 grey scale image is selected for quality evaluation. Image compression using different approximate booth multipliers are analyzed and output images are shown in Figure 2.

5 Performance analysis

The proposed R8ANBM multiplier and the existing multipliers are designed and simulated using Xilinx ISE 13.2 and these are coded using Verilog HDL. The performances of the proposed R8ANBM are analyzed in terms of area, delay and energy efficiency.

Table 2: Gate count of booth encoders

Technique	Number of logic gates
Conventional booth encoding	38
R8ABE1	35
R8ABE2	34
R8ABE3	35
R8ANBE	31

Area is analyzed in terms of number of 4 input LUTs, occupied slices and number of logic gates. Area of the proposed ANBE is compared with the existing booth encoding approaches and it is tabulated in Table 2. From Table 2, it is cleared that the proposed ANBE requires a smaller number of logic gates which is lesser than other existing approaches. R8ANBE has 22.58%, 12.90%, 9.67% and 12.90% less gate count than conventional booth encoding, R8ABE1, R8ABE2 and R8ABE3 respectively.

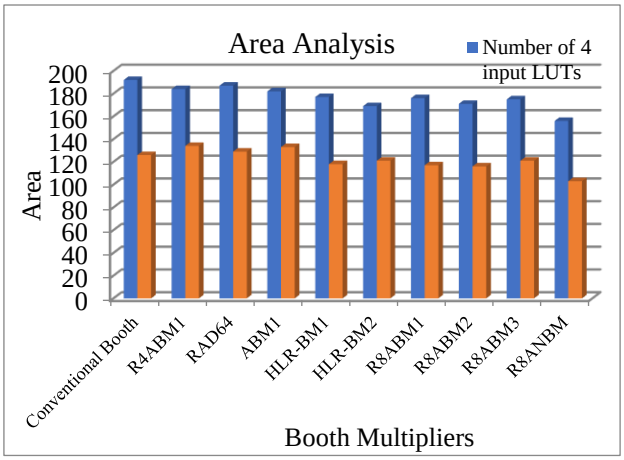


Figure 6: Area analysis of approximate booth multipliers

Area of the proposed radix-8 approximate multiplier using novel booth encoder is compared with the existing booth multipliers and it is shown in Figure 3. From the comparison chart, it is observed that, the proposed ANBE reduced the area over ther existing multiplier designs. The proposed R8ANBE reduced the number of 4 input LUTs by 23.07%, 17.94%, 19.87%, 16.66%, 13.46%, 8.33%, 12.82%, 9.61%, 12.17% and number of occupied slices by 22.33%, 30.09%, 25.24%, 29.12%, 14.56%, 17.47%, 13.59%, 12.62%, 17.47% when compared with the existing techniques such as conventional booth multiplier, R4ABM1, RAD64, ABM1, HLR-BM1, HLR-BM2, R8ABM1, R8ABM2, R8ABM3 respectively.

Time consumed by the different approximate multipliers to complete the operation is expressed in the comparison chart and it is shown in Figure 4. The proposed R8ANBM has reduced the delay by 31.86%, 29.24%, 27.91%, 30.94%, 27.51%, 24.87%, 16.03%, 18.45% and 18.88% when compared with the existing techniques such as conventional booth multiplier, R4ABM1, RAD64, ABM1, HLR-BM1, HLR-BM2, R8ABM1, R8ABM2 and R8ABM3 respectively.

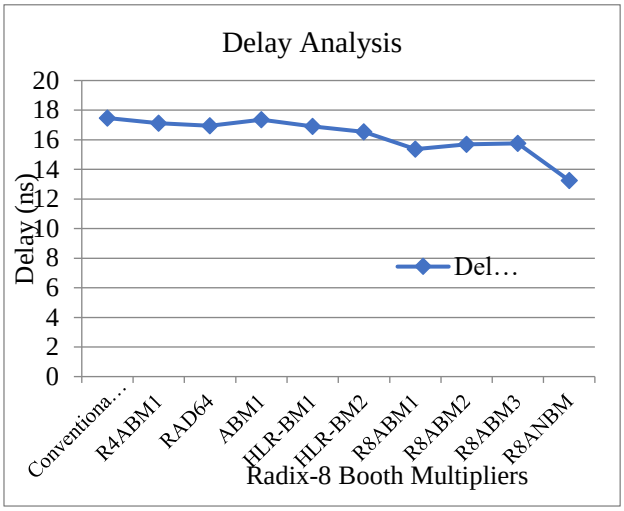


Figure 7: Delay analysis of approximate booth multipliers

Energy consumption of the approximate multiplier design is the power delay product. Energy consumption of various approximate booth multipliers are compared and it is tabulated in Table 3.

Table 3: Energy consumption comparison of approximate booth multipliers

Technique	Energy Consumption (nJ)
Conventional Booth	4.917
R4ABM1 [20]	4.521
RAD64 [21]	3.895
ABM1 [22]	3.567
HLR-BM1 [3]	3.125
HLR-BM2 [3]	2.992

R8ABM1 [23]	2.736
R8ABM2 [23]	2.557
R8ABM3 [23]	2.667
Proposed R8ANBM	2.132

From the tabulated results, it is observed that the proposed R8ANBM reduces the energy consumption by 56.64%, 52.84%, 45.26%, 40.22%, 31.77%, 28.74%, 22.07%, 16.62% and 20.05% when compared with conventional booth multiplier, R4ABM1, RAD64, ABM1, HLR-BM1, HLR-BM2, R8ABM1, R8ABM2 and R8ABM3. The proposed R8ANBM performs better in terms of area, speed and energy consumption.

6 Error analysis

The error fed by the approximate novel booth encoder in the proposed approximate novel booth multiplier is analyzed in terms of normalized mean error distance (NMED), mean relative error distance (MRED), accuracy and peak signal to noise ratio (PSNR). These error metrics are based on error distance which can be computed by calculating the difference between exact product and inexact product. MED is defined as the average values of error distance for all possible input combimations. NMED is the normalization of MED values [24] and it can be computed by the following expression.

$$NMED = \frac{1}{2^{2n}} \sum_{p=1}^{2^{2n}} \left| \frac{ED_p}{\max ED} \right| \quad (6)$$

Here, n denotes the bit width of multiplicand and multiplier. EDp denotes the error distance value of pth input combination. Max ED denotes maximum error distance value of the outputs. MRED is defined as the mean value of the ratio of error distance to the exact output for all possible combination of inputs. It can be computed by the following expression.

$$MRED = \frac{1}{2^{2n}} \sum_{p=1}^{2^{2n}} \left| \frac{ED_p}{EO_p} \right| \quad (7)$$

Here, EO denotes the exact output at pth combination of input. The accuracy of the proposed R8ANMB is the ratio of number of exact outputs to the total number of outputs and it can be expressed as follows.

$$Accuracy\ (\%) = \frac{Number\ of\ exact\ outputs}{Total\ number\ of\ outputs} \times 100 \quad (8)$$

The accuracy of the design is directly proportional to the number of exact outputs. So, the accuracy is improved by increasing the number of exact outputs.

Table 4: Error analysis of approximate radix-8 booth multipliers

Technique	NMED (x10-3)	MRED (x10-2)	PRED	Accuracy (%)
Conventional Booth	0	0	100	100
R4ABM1	8.425	3.478	98.51	45.38
RAD64	4.790	4.001	99.58	41.12
ABM1	5.472	1.276	99.68	44.98
HLR-BM1	7.914	3.045	98.35	64.89
HLR-BM2	6.185	2.151	99.12	63.24
R8ABM1	5.221	1.221	99.54	55.26
R8ABM2	6.245	2.027	99.01	42.71
R8ABM3	8.174	1.764	99.41	59.54
R8ANBM	3.114	0.923	99.76	67.15

Error metrics in terms of NMED, MRED and accuracy of the proposed R8ANBM are compared with the existing approximation booth multipliers and it is tabulated in Table 4. The tabulated results showed that the proposed R8ANBM reduces the NMED by 63.03%, 34.98%, 43.09%, 60.65%, 49.65%, 40.35%, 50.13%, 61.90% and MRED by 73.46%, 76.93%, 27.66%, 69.68%, 57.08%, 24.40%, 54.46%, 47.64% when compared with R4ABM1, RAD64, ABM1, HLR-BM1, HLR-BM2, R8ABM1, R8ABM2, R8ABM3 respectively. The proposed R8ANBM achieves better accuracy than exisiting approximate booth multipliers. The conventional accurate booth multiplier achieves 100% accuracy. The proposed R8ANBM achieved the accuracy as 67.15% which was increased by 32.41%, 38.76%, 33.01%, 3.36%, 5.82%, 17.70%, 36.39% and 11.33% when compared with R4ABM1, RAD64, ABM1, HLR-BM1, HLR-BM2, R8ABM1, R8ABM2 and R8ABM3 respectively.

In image sharpening applications, PSNR is one of the error metrics used to evaluate the quality of the output images. PSNR is measured in decibel and it can be computed by the following expression

$$PSNR = 10log_{10}\left(\frac{max_p^2}{MSE}\right) \quad (9)$$

where, max p denotes the input image's maximum pixel value and MSE denotes mean square error value of the image.

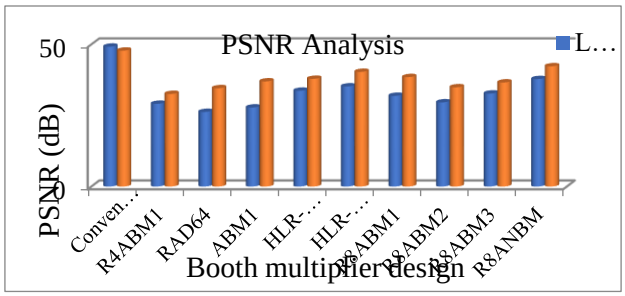


Figure 8: PSNR comparison of booth multipliers with two different test images

Image sharpening of radix 8 booth multipliers is tested with two different test iamges (Lena and Barbara) and its PSNR values are computed to show the effectivity of the proposed R8ANBM multiplier. From Figure 5, it is exhibited that, the proposed R8ANBM multiplier has low PSNR values compared with conventional booth multiplier and high PSNR values compared with another existing approximate booth multiplier. The proposed R8ANBM has 18.49%, 27.70%, 15.59% high PSNR for lena image and 9.87%, 21.20%, 15.57% high PSNR for barbara image compared to the existing approximate booth multipliers such as R8ABM1, R8ABM2, R8ABM3 respectively.

7 Conclusion

This paper talk about the approximate novel booth encoder design and radix-8 approximates novel booth multiplier based on ANBE. The accuracy of the proposed R8ANBM is high over other approximate booth multipliers, due to the less error probability of ANBE. Less number logic gates requirement in ANBE design leads to low area and low energy consumption in multiplier design. It also performs better in terms of NMER and MRED. The proposed R8ANBM reduces the NMED by 63.03%, 34.98%, 43.09%, 60.65%, 49.65%, 40.35%, 50.13%, 61.90% and MRED by 73.46%, 76.93%, 27.66%, 69.68%, 57.08%, 24.40%, 54.46%, 47.64% when compared with R4ABM1, RAD64, ABM1, HLR-BM1, HLR-BM2, R8ABM1, R8ABM2, R8ABM3 respectively. The proposed R8ANBM is analyzed for image sharpening applications. It can achieve high PSNR value as 37.8 for lena image and 42.3 for barbara image. The proposed R8ANBM achieved the accuracy as 67.15% which was increased by 32.41%, 38.76%, 33.01%, 3.36%, 5.82%, 17.70%, 36.39% and 11.33% when compared with R4ABM1, RAD64, ABM1, HLR-BM1, HLR-BM2, R8ABM1, R8ABM2 and R8ABM3 respectively. The proposed system is suitable for nanotechnology applications to reduce the power effectively.

Author contributions statement

"A. Azhagu Jaisudhan Pazhani done implementation of algorithms, methodology, preparation of flow chart and manuscript, result analysis for the manuscripts."

Conflict of interest

There is no conflict of interest in this paper regarding publication.

Data availability statement

The data that supports the findings of this study are available within the article.

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Back Propagation Neural Network-Enhanced Generative Model for Drying Process Control

Yonggang Liu*, Hongliang Zhang, Xiang Wei, Mei Li
Hebei Baisha Tobacco Co., Ltd. Baoding Cigarette Factory, Baoding 071000, China
E-mail: 15631295011@163.com
*Corresponding Author

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To improve the control precision and stability of the drying process, this work investigates a drying process control model based on a Back Propagation Neural Network (BPNN). The model includes a generative adversarial network framework, and combines the discriminator and generator structure of BPNN, optimizing their respective loss functions. It aims to solve the problem of insufficient sample space in the process parameters of the drying machine. The discriminator receives 7 key process parameters and uses a three-layer fully connected network for processing. The generator generates fake samples based on 7 process parameters. The model's performance is validated through experiments, including fit analysis of the generated results and the model's reliability analysis. The results show that the composite R^2 value of the data generation model reaches 0.93915 in the fit analysis. This consistency validates the model's ability to accurately fit the global data distribution, reflecting its generalization ability. The mean square error and mean absolute error are 0.275 and 0.185 respectively, which are better than other models, further verifying the model's performance. Additionally, significance analysis reveals that the H values of the process parameters in the datasets generated by the data generation model and the original datasets are all 0, with p-values greater than 0.05. This indicates no significant statistical difference between the two, confirming the reliability of the data generation model in filling the insufficient sample space. It suggests that the model can effectively enhance the completeness of the dataset without affecting the data distribution characteristics. The findings of this work provide theoretical and practical guidance for optimizing control in the drying process, contributing to improved control precision and stability in industrial drying operations.

Povzetek: Model za nadzor sušenja temelji na nevronski mreži s povratnim razširjanjem (BPNN) in vključuje generativni nasprotni okvir in združuje strukture diskriminatorja in generatorja BPNN za reševanje problema nezadostnega vzorčnega prostora. Rezultati kažejo, da model učinkovito povečuje nabor podatkov, ne da bi pri tem vplival na značilnosti porazdelitve podatkov.

1 Introduction

The drying process is one of the key steps in tobacco processing, and its control quality directly impacts the flavor and quality of the final product. Parameters such as temperature and humidity during the drying process must be precisely controlled to ensure that the tobacco leaves reach the desired moisture content and optimal physical properties [1,2]. However, due to the nonlinear and time-varying characteristics of the drying process, coupled with the complex environment in industrial production, traditional control methods, such as Proportional-Integral-Derivative (PID) control based on experience, often fail to achieve the desired results [3-5]. This makes achieving precise control of the drying process a pressing issue within the industry.

With the development of artificial intelligence technology, particularly the widespread application of neural networks in pattern recognition and process control, researchers have begun to explore their use in drying control [6]. The Back Propagation Neural Network (BPNN), a classic feedforward neural network, has been widely used in modeling and controlling complex industrial processes due to its powerful nonlinear mapping capabilities and adaptability [7,8]. However, the performance of neural network models depends on a large amount of high-quality training data. In actual production, due to the high cost of data collection or frequent changes in production batches, it is often difficult to obtain sufficient sample data. This limits the further application of neural network models in drying control [9,10]. Therefore, solving the problem of insufficient data samples has become the key to improving the neural networks' application effect.

Generative models like the Generative Adversarial Network (GAN) have gained widespread attention in the data augmentation field to overcome the issue of insufficient samples. Although these models have achieved remarkable results in areas such as image processing, their application in industrial process control is still in the exploratory stage. Specifically, in drying

control, generating high-quality synthetic process parameter data remains a challenging research topic.

Therefore, this work constructs a BPNN-based data generation model to address the insufficient sample issues in the drying process control. This model combines the BPNN's generator and discriminator structures to expand the training sample space by generating high-quality synthetic data, thereby improving the drying control model's performance.

The main contributions of this work are as follows:

(1) A data generation model for insufficient sample space of process parameters based on BPNN is proposed. By generating high-quality synthetic data, the model expands the training sample space, effectively solving the problem of data scarcity in drying process control.

(2) A generator and discriminator model based on BPNN is designed and optimized, significantly improving the accuracy and reliability of the generated data through detailed analysis of their network structures and optimization strategies.

(3) The effectiveness of the proposed model is validated through experiments, demonstrating its remarkable advantages in handling the under-sampling problem in the drying process. This provides a novel solution for the intelligent control of industrial processes.

2 Related work

In the field of drying control, the stability and quality of the drying process directly influence the flavor and quality of tobacco products. In recent years, more research has focused on exploring the application of intelligent control methods in the drying process. Mu et al. proposed an innovative humidity prediction method. This model transformed raw data into image data and used a multilayer convolutional neural network (CNN) for real-time prediction, successfully addressing the delay issues in traditional detection methods. Experimental results demonstrated that this method effectively predicted humidity and optimized the production process using real production data [11]. Furthermore, Odabas et al. introduced a correlated color temperature-based method to determine the optimal drying time for tobacco leaves. They found that the 17th day of drying yielded the best quality, with a correlated color temperature of 3000 K and a quality grade of 100% [12]. This method effectively guided the tobacco leaf drying process to ensure product quality. Similarly, Li et al. examined the relationship between thermal energy consumption and process parameters in tobacco drying using statistical analysis and machine learning. Their findings showed that reducing the main steam temperature significantly lowered energy consumption while optimizing other equipment parameters further improved energy efficiency [13]. This research provided valuable insights for green upgrading and energy conservation in tobacco manufacturing.

As research progresses and data scarcity in process control persists, generating high-quality synthetic data to improve model performance in under-sampled environments has become a hot topic. Zhou and Chiam proposed a new synthetic data generation strategy for knowledge distillation in regression tasks without original training data. By optimizing the bounded difference between student and teacher models, this strategy significantly improved the student model's performance, as confirmed by experimental results [14]. Barbierato et al. used probabilistic networks and structural equation modeling to address data bias, proposing a new synthetic dataset generation method. Validated on simple and loan approval datasets, this method effectively regulated bias and fairness with fewer parameters [15]. This method provided a powerful tool for developing and validating fair decision algorithms. Moreover, Zhang and Mikelsons introduced a novel sensitivity-guided iterative parameter identification and data generation algorithm, replacing traditional manual intervention. Using BayesFlow for parameter identification and a spatial variational autoencoder for data generation, the method remarkably accelerated the model calibration process. Experiments on a vehicle cabin thermal model showed that this method could greatly improve calibration accuracy and reduce calibration time from over a week to just one day [16]. This method effectively improved model calibration accuracy. The above studies have been summarized and compared with the method proposed in this work, resulting in Table 1:

Table 1: Comparison of existing methods with the proposed method

Research methods	**Data generation model**	**Main advantages**	**Limitations**	**The advantages of the proposed method**
Mu et al. [11]	Image data transformation + CNN	It improved humidity prediction accuracy and optimized the production process.	It was only applicable for humidity prediction and difficult to extend to other drying parameters.	The generation model proposed here can handle more drying process parameters and has wider applicability.
Odabas et al. [12]	Drying time prediction based on color temperature.	It provided effective recommendations for tobacco leaf drying time.	It was only suitable for predicting drying time,	The proposed method could adapt to more comple

			failed coping with the complex and variable drying process.	x drying processes by generating diverse process parameter data.
Li et al. [13]	Statistical analysis and machine learning	It offered effective guidance for energy conservation.	It mainly focused on the relationship between thermal energy consumption and parameters, neglecting dynamic control.	The proposed method could generate more dimensional process data, covering more variables to optimize drying control.
Zhou and Chiam [14]	Data generation strategy for knowledge distillation	It enhanced the learning effect of the student model.	It was primarily used for regression tasks and lacked customization for process control	This study applied synthetic data generation to the drying process, which exhibited higher industry adaptability.
Barbierato et al. [15]	Probabilistic networks and structural equation modeling	It controlled bias and fairness.	It was primarily used for regression tasks and lacked customization for process control.	This study applied synthetic data generation to the drying process, which exhibited higher industry adaptability.

In Table 1, existing methods generally exhibit several shortcomings. First, many methods are primarily designed for simplified datasets and single-task scenarios, lacking adaptability to complex industrial processes. Second, current methods often fail to ensure the interpretability of generated data and its high consistency with actual process parameters, resulting in significant discrepancies between generated and real data. Third, most synthetic data generation methods do not adequately consider the dynamic changes and multivariate characteristics of the drying process, leading to poor scalability in practical applications. Therefore, this work proposes a data generation model based on BPNN to handle the insufficient sample space of drying machine process parameters. By generating high-quality synthetic data, the model aims to expand the training sample space and improve the application performance of BPNN in the drying process. Compared with existing methods, the proposed model emphasizes practical applicability while focusing on the interpretability of the generated data and its close alignment with actual process parameters. Furthermore, the proposed model effectively handles complex, multivariate drying process data, thus overcoming the limitations of current methods in multidimensional data generation and process control.

3 The BPNN-based data generation model for drying machine process parameters with insufficient sample space

Accurate process parameter data is crucial for precise drying process control [17]. However, in practice, insufficient sample data often presents challenges for model development. To address this issue and enhance the application of BPNN in drying control, this work proposes a BPNN-based data generation model. The model aims to improve control accuracy in the drying process by generating high-quality synthetic data to expand the training sample space. Unlike traditional methods, this work focuses on solving data scarcity issues through advanced data generation techniques, providing a novel solution for intelligent drying process control. This section outlines the proposed data generation model's overall structure and key components.

3.1 Overall structure of the data generation model

GAN is a powerful tool for data generation through adversarial training. Here, the GAN's basic framework is used to construct the data generation model, producing high-quality drying machine process parameter data. The model's overall workflow is displayed in Figure 1 [18,19].

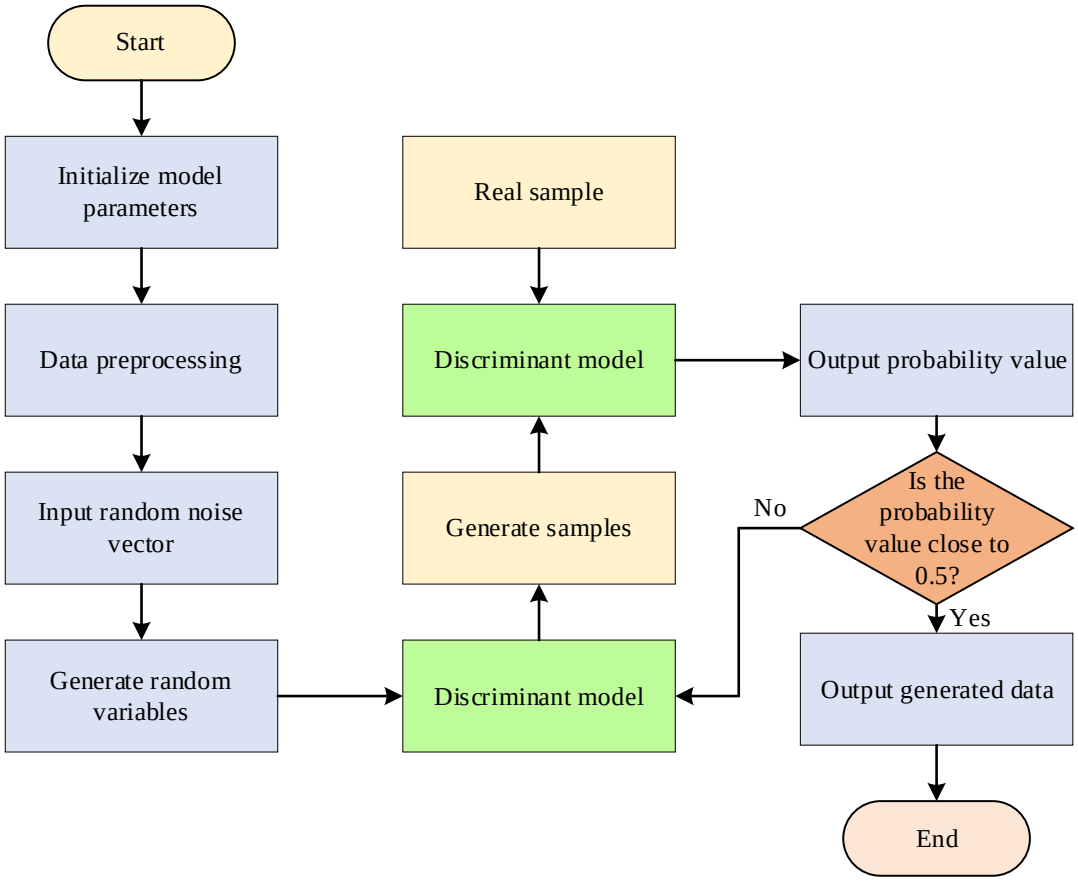


Figure 1: Workflow of the data generation model for drying machine process parameter

The workflow can be broken down into the following key steps:

(1) Data Initialization: In the initial phase of the model, a subset of samples is first extracted from the actual drying process dataset for subsequent training of the generator and discriminator. Data initialization involves randomly initializing the model parameters to start the training process. Additionally, a preprocessing step is applied to enhance training efficiency and data consistency, which often includes normalization. Normalization adjusts the values of each input data feature to a uniform range, typically [0, 1] or [-1, 1], which accelerates the convergence of model training and improves training performance.

(2) Generating Random Variables: The primary goal of the generator is to learn how to map random noise vectors into data samples that possess the characteristics of real samples. During this process, the generator receives a random noise vector as input, typically sampled from a Gaussian or uniform distribution. It then processes these random noise inputs through a neural network to generate new data samples. The objective is for these generated samples to exhibit distributional characteristics similar to those of the real data. The training goal of the generator is to progressively optimize its parameters to produce samples increasingly close to real data.

(3) Sample Mixing: To train the discriminator, the generated samples are mixed with real samples to form a training dataset. The discriminator's task is to distinguish which samples are fake, generated by the generator, and which come from real data. At this stage, the generator and the discriminator are adversarial. The generator aims to produce samples that the discriminator classifies as real, while the discriminator strives to identify the fake samples accurately. The mixed dataset includes real and generated fake samples for the discriminator's training.

(4) Discriminator Output Probability: The discriminator processes the input samples through a neural network and outputs a scalar probability value, representing the probability that a given sample is real. This probability ranges from 0 to 1. Ideally, the generator aims for its generated samples to yield probability values close to 1, meaning the discriminator misclassifies them as real samples. Conversely, for real data, the discriminator strives to output probabilities close to 0. The generator's objective is to make the discriminator classify its generated samples as real, resulting in probability values near 1.

(5) Training Objective Adjustment and Optimization: Based on the discriminator's output probabilities, the training objectives of both the generator and the discriminator are continuously adjusted. During each training iteration, if the discriminator's judgment on the generated samples approaches 50% (i.e., output probability near 0.5), indicating that the generated and real samples are nearly indistinguishable. In this case, the generator performs well and can continue optimization with its current parameters. However, if the

discriminator's output probabilities deviate significantly from 0.5, it implies poor sample quality from the generator. The discriminator's loss is then backpropagated to the generator, prompting parameter adjustments to enhance its performance. Through this adversarial training process, the generator and discriminator improve iteratively, with the generator progressively learning to produce more realistic data samples.

The above describes the detailed workflow of the data generation model for the drying machine process parameters illustrated in Figure 1. Each step aims to optimize the generator and discriminator through adversarial training, ultimately enabling the generated samples to closely resemble real data. Based on the above data processing in the generation model, the modeling process of the data generation model is obtained, as suggested in Figure 2.

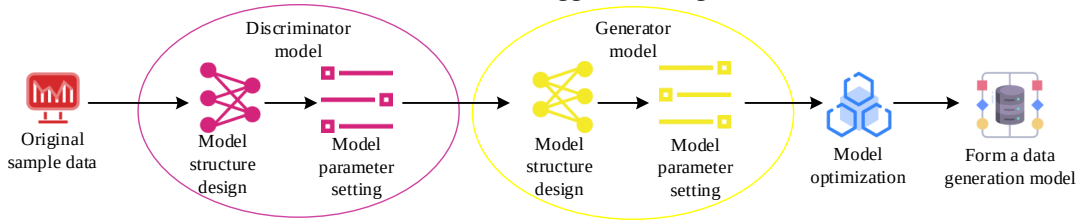


Figure 2: Modeling process of the data generation model for drying machine process parameters

3.2 BPNN-based discriminator and generator model network structure

In the data generation model, the design of the discriminator and generator is crucial for the quality and accuracy of the generated data. The discriminator evaluates whether the generated data matches the real data distribution, while the generator aims to produce fake data that aligns with the real distribution.

The main function of the discriminator is to perform binary classification between the fake samples generated by the generator and the real samples. Its input consists of a mixed dataset of fake samples generated by the generator and real samples of drying machine process parameters, which exhibit nonlinear relationships among the data groups. This dataset includes seven key parameters influencing the moisture content of the tobacco leaves during the drying process. They are the vent valve opening, drum wall temperature, moisture content of dried leaves, hot air temperature, steam valve opening of the drum wall, steam valve opening of the circulating air, and moisture content of cooled leaves [20-22]. The output value is a probability scalar indicating the likelihood that the generated fake sample data are classified as real. Due to the complex nonlinear relationships between these samples, the discriminator needs to have certain nonlinear mapping capabilities. Given the dataset's relatively low dimensionality and limited features, a three-layer fully connected BPNN is used as the discriminator. This network structure effectively handles simple binary classification tasks, performing both linear and nonlinear features, and ensuring the generated data meets accuracy requirements.

The generator's goal is to produce fake data that are consistent with the real data distribution. To achieve this, the generator's network structure must formalize the characteristics of the fake dataset it generates and possess strong nonlinear learning capabilities. The input and output data of the generator are analyzed. Its input consists of randomly generated noise data with the same number as the real dataset, and its output is the data processed by the generator network to be closer to the real values. Given that the input data is one-dimensional and relatively simple, a three-layer fully connected BPNN is employed for the generator.

The drying machine process parameter data have highly nonlinear characteristics. The BPNN's advantage lies in its strong nonlinear mapping capability. This allows it to automatically adjust structural parameters during training to establish complex input-output relationships without requiring an understanding of their intrinsic connections [23,24]. This makes it particularly well-suited for handling the nonlinear characteristics and intricate data relationships in drying machine process parameters. The three-layer network structure provides sufficient nonlinear representation capacity while avoiding overcomplicating the model. The design of a three-layer fully connected BPNN strikes a reasonable balance between computational efficiency and model complexity. Compared with deeper networks, the three-layer network has fewer parameters, reducing the risk of overfitting during training. This is particularly advantageous in the context of drying control, where the number of data samples is limited, as overly deep network structures may compromise the model's generalization ability. Additionally, the three-layer structure is relatively simple, efficiently performing linear and nonlinear mappings. Therefore, a three-layer fully connected BPNN is considered an effective choice for this work's tasks. Figure 3 presents the network structure of the discriminator and generator models based on BPNN.

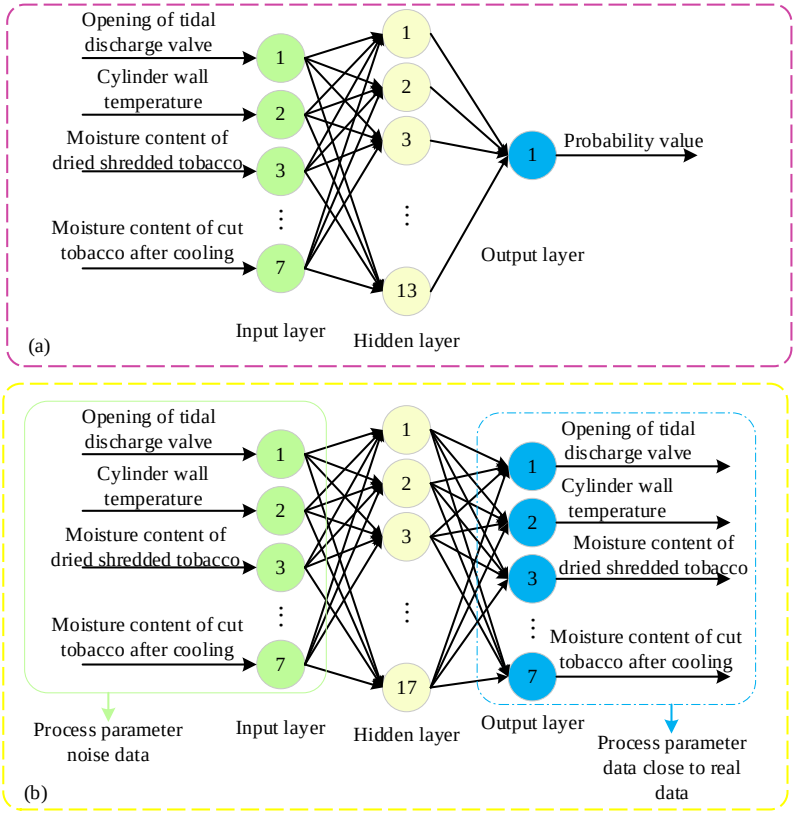


Figure 3: Diagram of the Discriminator and Generator Model Network Structure (a: Discriminator model structure; b: Generator model structure)

The pseudocode for the entire model is presented in Figure 4.

```
# Initialize the Generator and Discriminator
Initialize Generator
Initialize Discriminator

# Define the optimizers and loss functions
Define Generator Optimizer (e.g., SGD or Adam)
Define Discriminator Optimizer (e.g., SGD or Adam)
Define Generator Loss Function (e.g., Binary Cross Entropy)
Define Discriminator Loss Function (e.g., Binary Cross Entropy)

# Training process
for epoch in range(num_epochs):
    for batch in range(num_batches):
        # Get a batch of real samples
        Real_Samples = Get_Real_Samples(batch_size)

        # Generate fake samples
        Noise = Generate_Noise(batch_size)
        Fake_Samples = Generator(Noise)

        # Train the Discriminator
        # The Discriminator's goal is to label real samples as 1 and fake samples as 0
        Discriminator_Loss = Calculate_Discriminator_Loss(Real_Samples, Fake_Samples)
        Update_Discriminator(Discriminator_Loss)

        # Train the Generator
        # The Generator's goal is to make the Discriminator classify fake samples as real (label 1)
        Generator_Loss = Calculate_Generator_Loss(Fake_Samples)
        Update_Generator(Generator_Loss)

    # Output loss values for each epoch
    print("Epoch:", epoch, "Discriminator Loss:", Discriminator_Loss, "Generator Loss:",
Generator_Loss)

# Save the trained models
Save_Model(Generator, "trained_generator_model.pth")
Save_Model(Discriminator, "trained_discriminator_model.pth")
```

Figure 4: Pseudocode for model training

The carefully designed network structures of the discriminator and generator enable efficient data generation and classification, forming a robust foundation for modeling drying process parameters.

3.3 Optimization of the data generation model

Due to the intra-group data correlations and nonlinear characteristics between groups in the drying machine process parameter data with insufficient sample space, the original GAN model's loss function is not suitable for the subject of this work. Thus, optimizing the loss functions of both the discriminator and generator is crucial.

During the data generation model's operation, the discriminator and generator models are trained alternately. After each generator iteration, the discriminator model is optimized to achieve overall model improvement. The optimization goal of the model is to maximize the ability of the discriminator, which in turn drives the generator to produce more realistic data.

In the process of the data generation model, the discriminator and generator models are trained alternately. After each iteration of the generative model, the discriminator model is optimized to achieve the overall optimization of the model. The optimization process of the model can be expressed by equation (1):

$$\min_S \max_P H(P,S) = \mathbb{E}_{x-z_0}[\log P(x)] + \mathbb{E}_{c-z_c}[\log(1 - P(S(c)))] \quad (1)$$

x represents the real samples; c is the samples produced by the generator; z_0 refers to the distribution of real samples; z_c stands for the distribution of samples generated by the generator; $P(x)$ and $P(S(c))$ indicate the probability that the discriminator model classifies the real and generated samples as true; $\mathbb{E}$ denotes the expectation symbol; $\mathbb{E}_{x-z_0}$ means the expectation for real samples *x*; $\mathbb{E}_{c-z_c}$ represents the expectation for generated samples *c*.

The loss function for the discriminator enhances its ability to distinguish between real and generated samples by minimizing the probability of generated samples being classified as real.

In contrast, the generator optimizes the quality of its output by maximizing the discriminator's probability of misclassifying fake samples. The generator's goal is to produce fake samples that achieve the highest possible score from the discriminator, effectively deceiving it into classifying the fake samples as real. Thus, the generator's loss function is formulated as follows:

$$F_S = -\frac{1}{m}\sum_{i=1}^{m} \log(P(S(c^i))) \quad (2)$$

m represents the number of samples; c^i represents the ith generated sample; $P(S(c^i))$ denotes the probability that the discriminator predicts the generated sample c^i as a real sample. The generator aims to minimize this loss function, ensuring its fake samples are increasingly likely to be judged as real by the discriminator. The discriminator's primary task is to distinguish real data from generated data, and its loss function is designed to accurately evaluate the similarity between generated and real samples. In the original GAN model, the loss function is typically based on cross-entropy loss, calculating the binary classification probability between generated and real samples. The loss function for the discriminator reads:

$$F_P = -\frac{1}{m}\sum_{i=1}^{m} \log P(x^i) - \frac{1}{m}\sum_{i=1}^{m} \log(1 - P(S(c^i))) \quad (3)$$

For the discriminator in the data generation model, an input x without a label is obtained. Since there are no labels and it is unknown whether the input is a real sample or a generated fake sample, the contribution $Q(x)$ to the loss function of the data generation model is given by:

$$Q(x) = -z_0(x) \log P(x) - z_c(x) \log[1 - P(x)] \quad (4)$$

$z_0(x)$ and $z_c(x)$ represent whether sample x belongs to the real data distribution z_0 or the generated data distribution z_c, respectively; $P(x)$ denotes the probability assigned by the discriminator to sample x being real. By solving the derivative of $Q(x)$ with respect to $P(x)$, the optimal decision condition for the discriminator is obtained:

$$-\frac{z_0(x)}{P(x)} + \frac{z_c(x)}{1-P(x)} = 0 \quad (5)$$

Further simplification, the optimal discriminator decision function is obtained:

$$P^*(x) = \frac{z_0(x)}{z_0(x)+z_c(x)} \quad (6)$$

Analyzing the optimal discriminator, if $z_0(x) = 0$ and $z_c(x) \neq 0$, the optimal discriminator sets the probability to 0, indicating that the discriminator incorrectly classifies real samples as fake. If $z_0(x) = z_c(x)$, the discriminator considers the sample to have a 50% chance of being either a real or fake sample, resulting in an output of 0.5.

To further improve model performance and address the vanishing gradient problem during generator training, Jensen-Shannon (JS) divergence is introduced to measure the similarity between the real distribution N and the generated distribution W. JS divergence effectively quantifies the difference between two probability distributions and is defined as:

$$\begin{cases} KL(z_1 \| z_2) = E_{x-z_1} \log \frac{z_1}{z_2} \\ JS(z_1 \| z_2) = \frac{1}{2} KL\left(z_1 \left\| \frac{z_1+z_2}{2}\right.\right) + \frac{1}{2} KL\left(z_2 \left\| \frac{z_1+z_2}{2}\right.\right) \end{cases} \quad (7)$$

KL represents the Kullback-Leibler Divergence. By applying JS divergence, the optimized form of the generator's loss function is derived:

$$\min_S \max_P H(P,S) = 2JS(z_0 \| z_c) - 2\log 2 \quad (8)$$

This improvement not only mitigates the vanishing gradient problem for the generator but also enhances the similarity between the distributions of the generated and real samples.

To address the vanishing gradient issue, the loss function is further simplified by removing the logarithmic operation. The optimized loss functions for the discriminator and generator are as follows:

$$\begin{cases} F_P = -\frac{1}{m}\sum_{i=1}^{m} P(x^i) - \frac{1}{m}\sum_{i=1}^{m}[1 - P(S(c^i))] \\ F_S = -\frac{1}{m}\sum_{i=1}^{m} P(S(c^i)) \end{cases} \quad (9)$$

These optimization measures are aimed at enhancing the training effectiveness of the generator and discriminator, overcoming the gradient vanishing problem

in GAN, and ultimately generating higher-quality drying machine process parameter data.

4 Model performance validation

4.1 Experimental setup

The model is trained and validated using the Matlab platform in this experiment.

The dataset used in the experiment includes both real drying machine process parameter data and generated noise data. The real dataset comprises multiple samples of drying machine process parameters collected from actual operations, reflecting authentic conditions across various drying scenarios. Collecting these data involves gathering process parameters from a real production environment, followed by detailed annotation and processing. The generated noise data are produced by the generator network, to mimic the characteristics of the real data distribution. By inputting random noise into the generator, the network learns to generate samples similar to the real data, continuously optimizing the quality of the generated data. These noise data are used during training to challenge the real samples, driving the generator to produce data closely resembling the real samples.

First, the real training samples are imported into the Matlab environment, and all of these real samples are labeled as "1" to represent positive samples. Simultaneously, the noise samples generated by the generator are labeled as "0" to denote negative samples. This labeling setup ensures a clear distinction between real and generated data, effectively training the discriminator and generator models. Table 2 provides the parameter settings for the data generation model used in the experiment:

Table 2: Experimental parameter setting

Model	Parameter Name	Value
Discriminator	The Number of Input Layer Neurons	7
	The Number of Hidden Layer Neurons	13
	The Number of Output Layer Neurons	1
	Batch Size	62
	Initial Learning Rate	0.00001
	Optimizer	SGD Optimizer
Generator	The Number of Input Layer Neurons	7
	The Number of Hidden Layer Neurons	14
	The Number of Output Layer Neurons	7
	Batch Size	62
	Initial Learning Rate	0.00001
	Activation Function	Sigmoid
Overall Model	Iterations	30000

The input to the discriminator consists of seven key parameters from the drying machine process that primarily affect the moisture content of the tobacco leaves. Hence, the number of neurons in the input layer is 7, while the output is a probability value, so the output layer contains one neuron. The number of hidden layer neurons is determined based on the input and output layer neurons using equation (10):

$$Z = \sqrt{i + j} + a \tag{10}$$

i and j represent the number of input and output layer neurons; a refers to a constant in the range [0,10], set to a=10. Using this equation, the number of hidden layer neurons for the discriminator is calculated to be 13. Given that the dataset contains 309 highly nonlinear samples, conventional full-dataset and online learning approaches are not suitable. To improve training accuracy while maintaining reasonable training time, the batch size is appropriately reduced based on the full dataset. In this experiment, the 309 real samples are divided into five groups, setting the batch size to 62. This configuration retains sufficient data characteristics to effectively guide model optimization while avoiding overly large data inputs that could slow training or overburden computational resources, ensuring the efficiency of the training process. Due to the activation function of the hidden layer being Sigmoid, the initial setting of the learning rate requires a small value to meet the changing requirements of the learning rate. Therefore, the initial learning rate is set to 0.00001.

The number of neurons in the input layer of the generator is determined by the number of input parameters. The input consists of the process parameters with missing data and the process parameters that are related to them, totaling seven process parameters. Therefore, the number of neurons in the input layer is 7. The number of neurons in the output layer corresponds to the number of generated samples. To ensure the accuracy of the generator's learning, the output layer should have the same number of neurons as the input layer, hence the output layer also has 7 neurons. Similarly, using the equation, the number of neurons in the generator's hidden layer is calculated to be 14. The batch size of the generator is determined by the number of groups of input data. After excluding the samples with missing data, 310 valid samples are remaining. These valid samples are divided into 5 groups, with 62 samples per group, and the data are fed into the generator network. Consequently, the batch size for the generator is set to 62. The data preprocessing steps in the experiment include normalization to ensure that the values of each parameter are within a similar range. This helps to enhance the model's training effectiveness and convergence speed. All experimental data are standardized and split into training and testing sets in a 3:1 ratio, ensuring the reliability and reproducibility of the model's training and validation results.

In this work, the model may encounter overfitting issues. To prevent this, early stopping is employed to enhance the model's robustness and generalization ability. During training, the error on the validation set is monitored, and if the error no longer decreases over several consecutive training rounds, the training is stopped early to prevent overfitting on the training set.

4.2 Analysis of the fit of the data generation model's output

Figure 5 shows the fit of the training set.

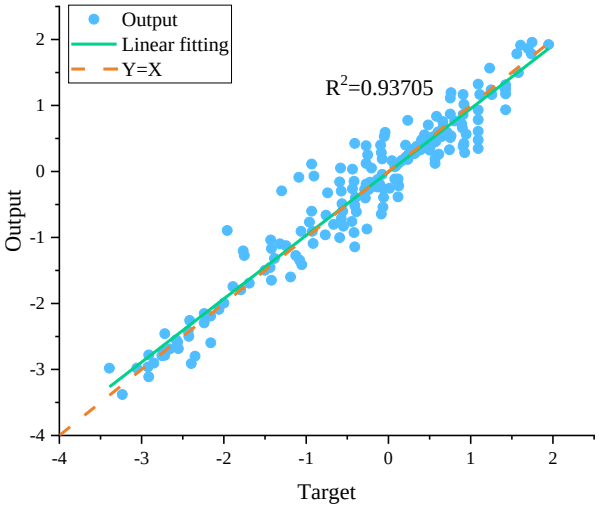


Figure 5: The fit of the data generation model on the training set

Figure 5 reveals that the model exhibits an optimal fit. Specifically, the R^2 value reaches 0.93705, indicating that the generative model effectively captures the distribution characteristics of the sample data within the training set. An R^2 value approaching 1 suggests a high correlation between the generated and actual sample data within the training set, demonstrating that the model has accurately learned and replicated the features of the real data.

Figure 6 displays the fit of the data generation model on the testing set.

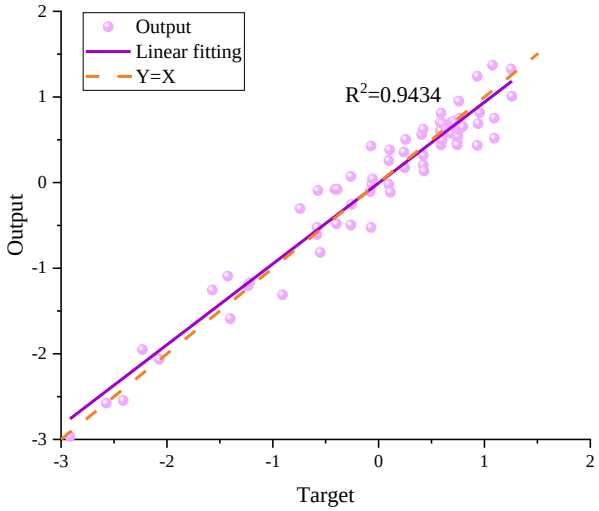


Figure 6: The fit of the data generation model on the testing set

The fit curve of the data generation model on the testing set, as shown in Figure 6, demonstrates that the model also performs exceptionally well on the testing data, with an R^2 value reaching 0.9434. This result indicates that the generative model can accurately replicate the distribution characteristics of real data, even when applied to previously unseen data, reflecting the model's strong generalization ability.

Analyzing the model's fit across the training and testing sets provides an overall assessment of its performance on the entire dataset. Figure 7 depicts the results.

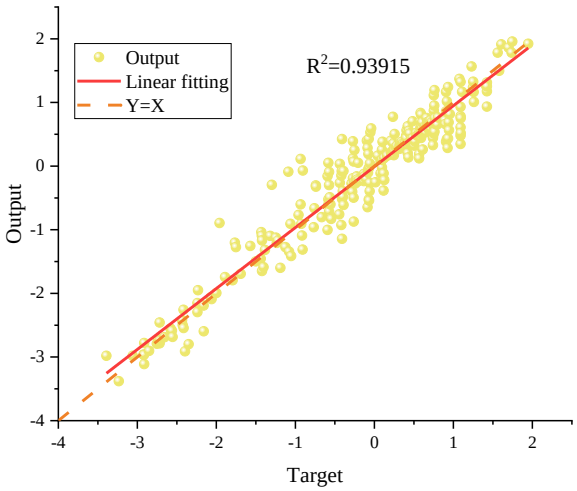


Figure 7: The overall fit of the data generation model

Figure 7 shows the overall fit of the data generation model. The results demonstrate the model's robustness and generalizability across the entire dataset. By analyzing the training and testing sets, the model maintains a high fit accuracy across a broader sample space, achieving an R^2 value of 0.93915. This indicates that the model effectively captures patterns in the training data and extends these patterns when encountering unseen test data. As a result, the quality and authenticity of the generated samples are preserved. This consistency confirms the model's robust ability to fit the global data distribution, highlighting its generalization ability.

4.3 Reliability analysis of the data generation model

After completing the training, the data generation model is used to interpolate samples into the under-sampled space of the drying machine process parameters. To verify the reliability of the data generation model, a significance analysis is conducted comparing the interpolated new data with the original dataset. This aims to ensure that the interpolated samples are consistent with the original samples in data distribution. Specifically, the significance of seven process parameters is tested at a 0.05 significance level to determine whether the interpolated data can preserve the distribution characteristics of the original dataset.

In the significance analysis, the null hypothesis is that the new and original datasets share the same data distribution at a significance level of 0.05. The H values and p-values for each process parameter are obtained by calculating the significance test parameters, as denoted in Figure 8.

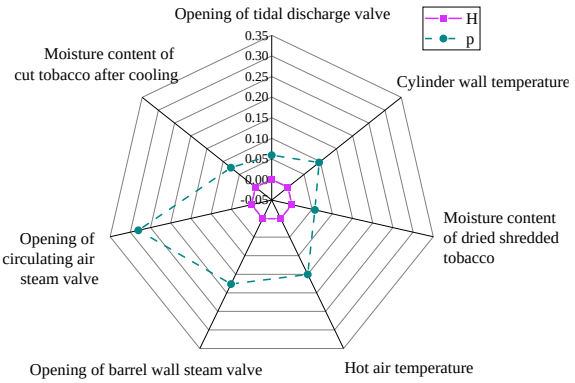


Figure 8: Significance test of the data generation model

In Figure 8, the H values for all process parameters are 0, and the p-values are greater than 0.05. There is insufficient evidence to reject the null hypothesis at the specified significance level. Therefore, it can be inferred that there is no statistically significant difference between the new and original datasets. Specifically, the significance test results for each process parameter demonstrate that the interpolated data statistically aligns with the original data's distribution. This outcome verifies the data generation model's reliability, showing that the generated interpolated values successfully learn and preserve the data distribution characteristics of the original sample space. Consequently, the data generation model is highly reliable in filling under-sampled spaces, effectively enhancing the dataset's completeness without altering its distribution characteristics.

An ablation experiment is conducted to evaluate the effectiveness of the loss function optimization. Model-1 represents the original model; Model-2 represents the model without optimization of the discriminator's loss function; Model-3 represents the model without optimization of the generator's loss function; Model-4 represents the model with neither the discriminator nor the generator optimized. The performance is evaluated using the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) as metrics, and the results are indicated in Figure 9.

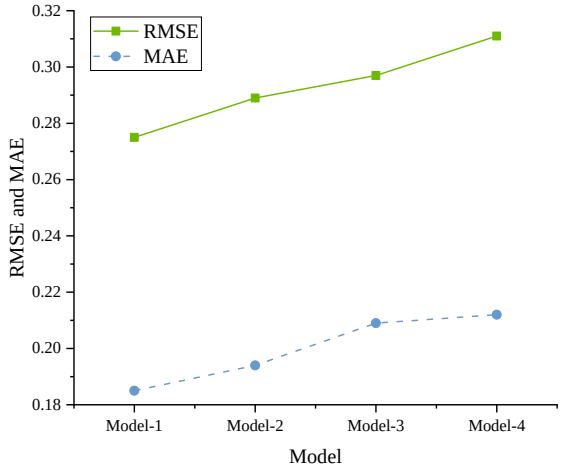


Figure 9: Results of the ablation experiment

As observed from Figure 9, model optimization significantly improves the quality of generated data. Model-1 performs the best in terms of RMSE and MAE, with values of 0.275 and 0.185, respectively. The removal of optimization for the discriminator and generator loss functions results in a decrease in performance. In Model-4, where neither the discriminator nor the generator's loss function is optimized, the performance is the worst, with RMSE and MAE values of 0.311 and 0.212, respectively. Overall, optimizing the loss functions leads to a significant improvement in model performance, particularly when both the discriminator and the generator are optimized simultaneously, which maximizes the precision of data generation.

To further validate the effectiveness of the model, this work compares the proposed model with several traditional modeling methods for drying machine process parameters. These methods include Support Vector Machine (SVM), Random Forest (RF), and Multi-Layer Perceptron (MLP), among other classical machine learning models. The results are listed in Table 3.

Table 3: Comparison of different models

Model	RMSE	MAE
The proposed model	0.275	0.185
SVM	0.307	0.215
RF	0.292	0.204
MLP	0.285	0.198

Table 3 shows that the proposed model outperforms the SVM, RF, and MLP models in terms of both RMSE and MAE. This indicates that the optimized BPNN model can better capture the complex nonlinear relationships in the drying process. It generates samples that are closer to real data, particularly demonstrating superior performance on the test set with strong generalization ability.

In addition, to further evaluate the model's robustness and the repeatability of the results, cross-validation is conducted. By employing a 5-fold cross-validation method, the model undergoes multiple rounds of training and validation to reduce the possibility of overfitting and ensure the stability of the results. The cross-validation results reveal that the model's performance is consistent across all folds, with a standard deviation of the R^2 value of only 0.0025, further demonstrating the model's robustness and reliability under different data splits.

4.4 Discussion

In this work, the proposed BPNN-based data generation model for drying machine process parameters with insufficient sample space achieves promising results in the experiments. Specifically, the model's R^2 value on the training set is 0.9322, and on the test set, it is 0.9434. The combined R^2 value for the training and test sets reaches 0.93915, indicating that the model has good generalization ability within the sample space. To compare the results of this work, the experimental outcomes are contrasted with existing data generation methods in the literature. Zhou and Chiam [14] proposed a synthetic data generation strategy for the MNIST regression task, with an MAE of

1.179 and an RMSE of 1.978, significantly outperforming traditional random sampling and generator methods. Although this method demonstrates significant performance in simpler tasks, its limitation lies in its primary applicability to simplified datasets and tasks. It has not been sufficiently validated for complex process control and high-dimensional data generation in multi-variable scenarios. In contrast, the proposed method optimizes the generation of multi-dimensional, multi-variable parameters in the drying process. The model achieves high R^2 values on the training and test sets, indicating strong adaptability to real process data. Barbierato et al. [15] proposed a synthetic dataset generation method for a simple dataset with six features, evaluating the impact of mutual information between the features. This method focuses on single-dimensional data generation and adjusting feature importance, making it suitable for relatively simple decision-making problems. Compared to this, the proposed model can generate more complex multi-dimensional data while considering the interdependencies among process parameters in the drying process, offering higher industrial application value. By validating the model's fitting accuracy across a broader sample space, the proposed model demonstrates better scalability and reliability than the method of Barbierato et al. Zhang and Mikelsons [16] presented a data generation algorithm. This algorithm performed well in calibration models, achieving a mean relative error rate of 1.62% for all parameter estimates and an MAE of 0.108°C for the calibration model's output. This method effectively improves calibration accuracy and reduces calibration time. However, its core focus is on model calibration, primarily applied to a few variables such as temperature, limiting its use in complex multi-variable drying control problems. In contrast, the proposed generation model demonstrates high fitting accuracy and handles multiple process parameters in the drying process. Moreover, significance analysis is conducted on the generated data, verifying its reliability and statistical consistency with the original data. This ensures the effectiveness and practicality of the generated data for more complex control tasks.

Through comparison, it is evident that existing methods have achieved good results in simpler tasks or specific control scenarios. However, they often face challenges such as inadequate adaptability, poor interpretability, or a disconnect between generated data and actual process data when addressing multi-dimensional, complex process data. The BPNN-based data generation model for drying machine process parameters with insufficient sample space proposed in this work effectively expands the training sample space. Meanwhile, it improves the generation quality of multi-variable parameters and maintains high fitting accuracy across a broader sample space. Through comprehensive analysis of the training and test sets, the model demonstrates strong generalization ability and robustness.

However, despite the strong performance of the proposed method in several aspects, there are still some limitations. First, although the proposed model performs well with existing process parameter data, its generation capabilities may be limited when facing entirely new or unseen process conditions. Particularly, in extreme or special process scenarios, the generated data may not fully reflect the details of the actual process. Therefore, future work could focus on enhancing the adaptability of the generation model to handle more variable and complex process parameter spaces. Second, despite improving the quality of generated data through optimization of the generator network structure, the interpretability of the data generation process remains a challenge. In practical applications, ensuring strong interpretability between the generated data and the process parameters in actual production remains a crucial area for future research.

Overall, the proposed model has demonstrated good performance in enhancing the accuracy and stability of the drying process control. Compared to existing methods, the proposed model better accommodates the multidimensional and multivariable data generation requirements of the drying process, showing high fitting accuracy on both the training and testing datasets. Nevertheless, the generative model has certain limitations when dealing with extreme process conditions or special data requirements. Future research should focus on further optimizing the adaptability and interpretability of the data generation algorithm to better support drying control in actual production settings.

In practical applications, although the proposed method has yielded favorable results in generating drying process parameter data, significant differences in the process characteristics of different industrial processes may exist. For example, some industrial processes may involve more complex nonlinear relationships or multivariable interactions, which could increase the difficulty of model training. In these cases, further adjustments to the network structure of the generator and discriminator may be necessary to accommodate specific data distributions and process requirements. Additionally, data distributions under different operating conditions may vary. Factors such as changes in the production environment, equipment aging, and raw material differences can all affect the data generation and prediction performance. The model's stability and robustness may be tested under these variations, making it critical to adjust model parameters in response to new operating conditions to maintain the quality of generated samples. In this regard, adaptive training strategies or online learning methods may need to be introduced to allow the generative model to adapt to environmental changes in real-time. Moreover, the quality and quantity of the data are also significant factors affecting the model's generalization ability. The data generation model used in this work assumes that the input data is of high quality and sufficiently diverse. However, in some industrial scenarios, data may be missing, noisy, or incomplete, which can affect model training and prediction outcomes. Therefore, additional denoising and data supplementation strategies may need to be incorporated during the data preprocessing stage to ensure data quality and improve the model's generalization ability. In conclusion, although the proposed model performs well in drying control, it still requires appropriate adjustments and optimization when

applied to other industrial processes or under different operating conditions.

5 Conclusion

This work proposes a BPNN-based data generation model to address the insufficient sample space for drying machine process parameters. It demonstrates the model's effectiveness in expanding the training sample space and improving drying control through experiments. The following conclusions are drawn. (1) The constructed data generation model achieves a fitting R^2 of 0.93705 on the training set and an R^2 of 0.9434 on the test set. This indicates that the model performs well in the training set and maintains high predictive accuracy in the test set. (2) By integrating data from the training and test sets, the model maintains a high fitting accuracy across a broader sample space, with an R^2 value of 0.93915. This reveals that the model effectively captures patterns in the training data and extends these patterns to unseen test data, ensuring the quality and authenticity of the generated samples. (3) Significance analysis shows that the H values for all process parameters are 0, and the p-values are greater than 0.05. It illustrates that generated dataset shows no significant statistical difference from the original, validating the model's reliability.

The proposed BPNN-based data generation model has achieved relatively ideal experimental results in generating and controlling drying machine process parameter data. However, its adaptability under diverse production conditions still requires further research and validation. In actual production environments, process conditions often experience significant fluctuations, such as variations in raw materials, equipment aging, and environmental temperature changes, which may impact the model's performance. Therefore, future research could consider incorporating a wider range of production conditions for validation, especially under high noise, dynamic changes, or extreme operating conditions, to comprehensively assess the model's stability, adaptability, and generalization ability. For instance, testing the model's performance under different seasons, production batches, or equipment scenarios could further validate its effectiveness in complex and dynamic production environments.

Furthermore, the proposed method primarily relies on a fixed process parameter dataset, whereas different industrial processes, equipment, and production lines may exhibit substantial differences in parameter settings, production environments, and data characteristics. Hence, the model's cross-domain adaptability can be an important focus of future research. To address this, it should explore methods such as multi-task learning and transfer learning to enhance the model's self-adaptive ability under varying process conditions and production environments, thereby handling the heterogeneity of different industrial processes. Additionally, the proposed model has not been thoroughly validated in scenarios where data quality is lacking or missing. In practical applications, data may be incomplete, missing, or subject to high noise interference, which can significantly affect the model's training outcomes. Future research could explore data preprocessing, missing data imputation, and adaptive algorithms to improve the model's robustness under conditions of unstable data quality.

Additionally, although the proposed model performs well under conditions of high-quality data, its robustness still needs further improvement in environments with poor data quality, high missing values, or significant noise. Therefore, future research could focus on exploring ways to enhance the model's performance under incomplete data conditions by introducing data preprocessing techniques, missing data imputation, or adaptive algorithms. These approaches can help the model address more complex real-world application scenarios, improving its stability and accuracy.

Regarding the selection of model architecture, this work employs the traditional BPNN architecture, which performs well in handling nonlinear data. However, for more complex and dynamic data, other architectures, such as deep CNNs or long short-term memory networks, may perform better in capturing temporal relationships and local features. Therefore, future research should consider a comparison and selection of various neural network architectures, examining the strengths and weaknesses of different architectures under various process conditions. Meanwhile, it should discuss the specific constraints faced in architecture selection, such as computational resources, training time, and model complexity.

In conclusion, future research could further deepen in the following areas. First, the model's adaptability testing is expanded to cover a wider range of production conditions, particularly considering the impact of complex environments such as high noise and dynamic changes on model performance. Second, cross-domain data generation and optimization issues under different process conditions and production environments are considered to enhance the model's adaptability to heterogeneous data. Finally, the challenges of unstable data quality are addressed by further exploring optimizing data preprocessing, and advanced missing data imputation techniques are adopted to strengthen the model's robustness and stability. With these improvements, future work could further enhance the model's adaptability and robustness, providing more reliable and universal technical support for data generation and process control in intelligent systems.

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Detection of E-commerce Fake Reviews Using Core Diagram and Metric Weight Measurement Algorithms

Junsheng Song[1*], Chunyan Wu[2], Juan Li[3]
[1]Security Office, Shandong Labor Vocational and Technical CollegeJi'nan, 250022, China
[2]Department of Senior Technician, Shandong Labor Vocational and Technical College, Ji'nan, 250022, China
[3]Continuing Education Center, Shandong Labor Vocational and Technical College, Ji'nan, 250022, China
E-mail: sjs091240@163.com, yanzi691177@126.com, liyajing828@163.com
[*]Corresponding author

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In today's digital age, e-commerce platforms have become an essential part of daily life. However, the convenience and openness of online shopping has also led to numerous legal and ethical issues. Dishonest merchants, in pursuit of higher profits, often hire fake reviewers to post misleading comments, undermining consumer trust and violating trade laws. Therefore, in response to the detection of such fraudulent activities in the e-commerce environment, this study proposes a method that uses core diagrams and metric weight measurements to identify fake reviews. By evaluating the relevance of users based on rating levels and temporal correlation, a user relationship graph was constructed, which served as the basis for the detection algorithm. The method improved the accuracy of fake review detection by employing a multi-label propagation strategy and integrating an algorithm that combined entropy and analytic hierarchy process methods for metric weight measurement. The experimental setup was conducted on four real-world datasets—Amazon, YelpChi, YelpNYC, and YelpZip. The results showed that the proposed method achieved an average accuracy of 0.88, a precision of 0.88, a recall rate of 0.85, and an F1 score of 0.87 on the Amazon dataset, significantly outperforming other methods. These findings highlight the applicability and reliability of the model proposed in this study in the field of e-commerce fake review detection, providing a strong solution to protect consumer interests and maintain fair competition in the online market.

Povzetek: Razvita je metoda za zaznavanje lažnih ocen v e-trgovini, ki uporablja jedrne diagrame in algoritme merjenja uteži metrik. Z ocenjevanjem relevantnosti uporabnikov na podlagi ocen in časovne korelacije je bil zgrajen graf uporabniških odnosov. Metoda izboljšuje zaznavanje lažnih ocen z uporabo strategije propagacije z več oznakami in algoritma, ki združuje metode entropije in analitičnega hierarhičnega procesa za merjenje uteži metrik.

1 Introduction

With its characteristics of convenience, speed, and affordability, online shopping is gradually becoming the mainstream of mass consumption. With the proliferation of online shopping platforms, the content of reviews is growing at an astonishing rate, making it difficult for users to distinguish between real and fake reviews. In addition, the virtual and open nature of the Internet has led to numerous legal issues in online shopping [1]. Many unscrupulous merchants, driven by profit motives, engage in the dissemination of false evaluations online to promote their own products or denigrate competitors. In particular, fake reviews refer to the hiring of fake accounts to publish deceptive comments by certain enterprises, aiming to promote their own products or discredit those of competitors [2]. As review information is a crucial basis for consumer purchasing decisions, erroneous decisions can impact the legitimate interests of consumers. Allowing such behavior to proliferate would seriously harm consumer interests and jeopardize internet security [3]. As mentioned by Lecue F in his study, the existing methods are deficient in feature extraction and evaluation index weight assignment [4]. At the same time, they are also deficient in effectively identifying target users, which may lead to unsatisfactory recognition results. For example, Ji S. et al. pointed out in their study that existing methods such as support vector machines (SVM), random forests (RF), and convolutional neural networks (CNN) still had limitations in recognizing user behavior patterns [5]. These problems ultimately lead to unsatisfactory detection results. To further optimize the effectiveness of e-commerce fake review detection, this study proposes a method based on core diagram (CD) and metric weight measurement. The innovations of this research include following points. (1) Proposing a label propagation algorithm for fake review group detection based on CD.

(2) Addressing the disparity in the importance of various metrics in fake review group detection by introducing a metric weight measurement algorithm that integrates entropy method (EM) and analytic hierarchy process (AHP). This study is divided into four sections. (1) Literature review, which reviews the current status of CDs and existing fake review detection technologies. (2) Research methodology, which provides a detailed discussion of the core technologies in this study. (3) Experimental verification, which conducts simulation experiments on the proposed method. (4) Conclusion, which summarizes and provides future prospects for the entire research.

2 Related work

CD is a graph model composed of user relationships. Research on graph models has attracted attention from scholars across various fields. Berahmand K and colleagues proposed a novel CD algorithm and applied it to simulate the spread of popular epidemics. This algorithm had advantages such as linear temporal ordering, local information utilization, and independence from any parameters, making it one of the most popular community detection algorithms in recent years [6]. On a legal level, such algorithms can help identify groups of fake reviewers, provide evidence for legal proceedings. It can enhance the regulatory capacity of e-commerce platforms, and protect consumer rights. Compared to other advanced attribute graph clustering methods, this approach is more efficient and accurate. Graham S et al., building on the CD method, introduced a knowledge graph embedding model applied to detecting anomalous transactions in the trade of cultural artifacts. The study employed semantic annotation tools to construct a CD model related to cultural artifact trade. Through supervised machine learning, they transformed CD into a knowledge graph embedding model, demonstrating significant potential in uncovering concealed aspects of illegal cultural artifact trade [7]. Wang Y et al. proposed an indoor positioning system based on an adaptive robust factor CD model, suitable for smartphone indoor positioning. This method, grounded in CD, integrated Wi-Fi and PDR location information, effectively addressing issues such as low network update frequency, Wi-Fi coarse errors, and PDR error accumulation. It achieved precise positioning for multiple unknown points indoors [8]. Zhong Y et al. presented a CD partitioning algorithm based on heterogeneous perception. This method considered differences in network bandwidth, computing node capabilities, and resource competition among kernels in high-speed networks. Compared to existing methods, the proposed algorithm demonstrated improvements in distributed and heterogeneous clustering. Experimental results confirmed its effectiveness in addressing graph node allocation issues in distributed and heterogeneous clustering [9]. Feng L et al., approaching from the perspective of service trade, constructed a service trade network based on the CD model and complex network theory. This model proved useful for analyzing the openness of national service trade, urbanization rates, and mutual influencing factors [10].

The rapid development of e-commerce platforms has intensified competition among merchants, leading to a proliferation of fake reviews. Therefore, scholars from various fields have shown interest in methods for detecting fake reviews. Cheng J et al. proposed a semi-supervised generative adversarial network with an integrated attention mechanism for fake review detection. This model, incorporating an attention mechanism, exhibited ample semantic expressive capability and relied on a small number of labeled samples for detecting fake reviews. Experimental results indicated that when the number of labeled samples is limited, this method outperformed currently popular semi-supervised pseudo-review detection methods [11]. Bathla G et al. proposed a fake review detection method that combines CNN and LSTM networks, considering existing methods to be time-consuming and inefficient. This method effectively extracted user features from comments and utilizes user sentiment information for fake review identification. Experimental results demonstrated the superior performance of this method in handling complex computations [12]. Alsubari S et al. developed a fake review detection system based on n-grams and reviewer sentiment scores for more accurate detection of fake reviews. This method input n-grams of comment text into the constructed model, automatically identified user comments, and assessed their authenticity. Simulation experiments validated the superiority of the proposed method in terms of accuracy [13]. Vidanagama D et al. compiled prominent techniques proposed to address the fake review detection problem, aiming to provide a theoretical basis for subsequent fake review detection by analyzing existing methods in depth, clarifying their characteristics, advantages, and limitations [14]. Mutemi A et al. addressed the lack of research on fraud detection in e-commerce by conducting a systematic review and meta-analysis of preferred reporting items for research. By exploring the effectiveness of machine learning and data mining techniques for fraud detection in digital marketplaces and broader e-commerce environments, research opportunities were identified, providing industry stakeholders with insights into key technologies and trends [15].

In summary, the existing methods for detecting fake reviews are based on the CD model and have achieved good results. These studies provide different technical means to identify and combat fake review behavior in a legal context, thus protecting consumers from fraud and misinformation and maintaining a level playing field in the e-commerce marketplace. This is important for effective regulation by regulators with limited resources,

and provides technical support for identifying and proving fraudulent behavior in legal proceedings. However, existing studies have neglected the impact of fake review behavior on consumer rights and the competitive environment of the market, as well as how to effectively regulate and combat it through legal means. In addition, existing techniques do not take into account the different importance of evaluation indicators when identifying fake review groups, resulting in inaccurate and inefficient detection results. Therefore, this study aims to improve the effectiveness of fake review detection in e-commerce by proposing a method based on CD and metric weight measurement. A comparative summary of existing methods is shown in Table 1.

Table 1: Comparative analysis of existing methods

References	Methodology	Data sets	Inadequacies
Berahmand K et al [6]	CD	Epidemiological data	No consideration of comment content and user behavioural pattern analysis, limited applicability to the legal context
Graham S et al [7]	CD-based knowledge graph embedding model	Cultural artwork transaction data	Lack of in-depth research on anomalous transaction detection in a legal context
Wang Y et al [8]	Adaptive robust factor CD model	Smartphone data	High computational complexity
Zhong Y et al [9]	CD segmentation algorithm for heterogeneous sensing	High-speed network data	High computational complexity
Feng L et al[10]	CD modelling and complex network approach	One Belt One Road data	High computational complexity
Cheng J et al [11]	Semi-supervised generative adversarial networks	E-commerce review data	Dependent on a small number of labelled samples with limited generalisation ability
Bathla G et al [12]	A combination of CNN and LSTM networks	E-commerce review data	High computational complexity, low efficiency, difficult to cope with large-scale data sets
Alsubari S et al [13]	Based on n-gram and sentiment scores	E-commerce review data	Large errors in the detection of fake comments
This study	Detection of false e-commerce reviews based on CD and indicator weight metrics	Four labelled real datasets	-

3 E-commerce fake review detection model based on CD and metric weight measurement

To enhance fake review detection in e-commerce, this study proposes a CD-based label propagation algorithm for fake review group detection. Initially, the study constructs a CD-based label propagation fake review detection method. Subsequently, entropy weighting and AHP are introduced to measure the weights of various indicators of fake reviews.

3.1 CD-based label propagation algorithm for detecting fake review groups

Customer reviews on e-commerce platforms have a significant impact on consumer behavior. However, misleading reviews due to language bias can result in merchants making undue profits, violating commercial laws such as the Anti-Unfair Competition Law and the Consumer Rights Protection Law, and infringing on consumers' rights [16]. These laws clearly stipulate the principle of good faith in commercial activities and the basic rights of consumers, including the right to know and the right to choose. By providing false or misleading information, misleading reviews undermine the fair competitive environment in the market and harm the legitimate rights and interests of consumers, and therefore must be regulated and combated by legal means. The effective identification of false comments on the Internet is an urgent problem that demands resolution.

Despite the fact that a considerable number of studies have been dedicated to the identification of fake comment groups, extant methods include semi-supervised generative adversarial networks by Cheng J et al., Bathla

G et al.'s method combining CNN and LSTM, and Alsubari S et al.'s system based on n-grams and sentiment scores. These methods face efficiency bottlenecks when dealing with large datasets, complex computations, and distinguishing between similar fake comments, and have limited application in legal contexts because they fail to deeply analyze the content of comments and user behavior patterns [17]. Therefore, this study proposes a CD-based algorithm for detecting clusters of label-propagating fake comments. The method analyzes the ratings of users in fake review clusters for their characteristics, including abnormal consistency of ratings, temporal concentration, similarity of language patterns, and abnormal user behavior. Based on the analysis, the algorithm establishes a user relationship graph by examining the closeness between users through rating levels and temporal correlations. Subsequently, utilizing CD as a foundation and employing a multi-label propagation approach, the algorithm groups users in the graph, yielding candidate groups [18]. Finally, the algorithm uses multiple fake review group detection indicators to classify and identify fake review groups within these candidates. The research examines user relationships from two perspectives: similarity in review content and similarity in user behavior. The closer the relationship between two reviewers, the more likely they are to belong to the same fake review group [19]. The formula for calculating the correlation between a user's product rating and review time is presented in Equation (1).

$$tn(a,b,m)=\begin{cases}0, & \left|S_a^m-S_b^m\right|\geq 2\vee\left|t_a^m-t_b^m\right|>\tau\\ 0.5\times\left(1-\dfrac{\left|S_a^m-S_b^m\right|}{2}\right) & \\ +0.5\times\left(1-\dfrac{\left|t_a^m-t_b^m\right|}{\tau}\right), & otherwise\end{cases} \quad (1)$$

In Equation (1), S_a^m, S_b^m represent the ratings given by reviewers a,b for product m, while t_a^m, t_b^m) represent the review times of reviewers a,b for product m. The formula for calculating the closeness between reviewers is defined in Equation (2).

$$tns(a,b)=\frac{\left|P_a\cap P_b\right|}{\left|P_a\cup P_b\right|}\times\sum_{m\in P_a\cap P_b}tn(a,b,m) \quad (2)$$

In Equation (2), P_a represents the product reviewed by reviewer a, P_b represents the product reviewed by reviewer b, and $tn(a,b,m)$ represents the correlation between a user's product rating and review time. $tns(a,b)$ is mapped to the range $[0,1]$, as shown in Equation (3).

$$W(a,b)=\frac{2}{1+e^{-tns(a,b)}}-1 \quad (3)$$

In Equation (3), the correlation quantifies the extent to which two users share the same product review in the overall review. A higher percentage of reviewer a,b's sharing of the same product review implies that the two users are more correlated in their review behavior [20]. Given the high uncertainty in the label propagation process, the study, based on the CD method, assigns the same label to nodes within the same CD. Nodes not belonging to any of these cores are assigned an independent label. In graph theory, every weighted graph has a global density, and this study assumes that when the closeness of two nodes exceeds the graph's density, these nodes are considered to be on the same CD. The graph density is defined as shown in Equation (4).

$$\rho(WG)=\frac{\sum_{x,y\in V}W_{xy}}{\left|E\right|} \quad (4)$$

In Equation (4), WG represents the user relationship graph, which can reflect the average weight of the edges in the graph. Therefore, it can provide the algorithm with a measure of the closeness of the relationship between the nodes in the graph. V represents all nodes in the graph, and E represents all edges. W_{xy} represents the weight between nodes x and y. Therefore, the operation process of the CD algorithm is shown in Figure 1.

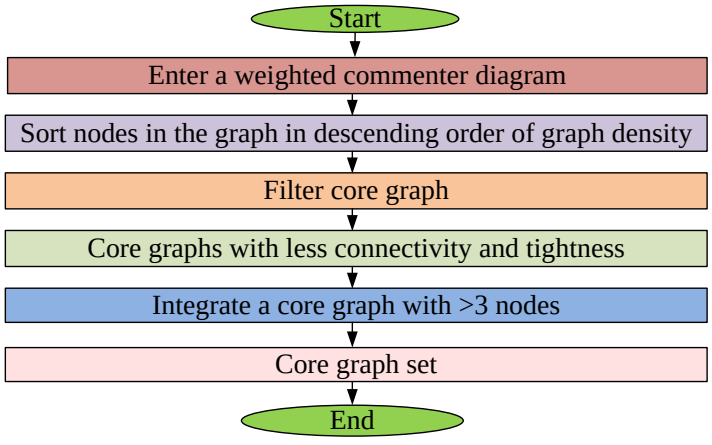


Figure 1: Operation process of CD algorithm

During label propagation, the strength of communication between nodes can be measured using the weights of the edges in the user-associated graph. For propagation, the connectivity between nodes is more important than propagation strength. Therefore, this study introduces *anklevalue* automatic label filtering to mitigate the impact of propagation strength [21-22]. *anklevalue* can identify points of sharp change in a sequence of numbers and filter them. It is assumed that the label ownership degree sequence is $(d_1,\ldots,d_i,\ldots,d_n)$, define two lines as le_1, le_2. Connect d_1 to d_i and d_n. Among them, d_i denotes the label ownership degree of the i th node. Label ownership degree is the likelihood or confidence that a node is assigned to a particular label. *anklevalue* can be represented as the maximum angle between the two lines, as shown in Equation (5).

$$\tan\theta = \left(\left|k_1 - k_2\right|\right) / \left(1 + k_1 \times k_2\right) \tag{5}$$

In Equation (5), k_1, k_2 represent the slopes of le_1, le_2, and their calculation formulas are given by Equation (6).

$$\begin{cases} k_1 = \left(d_i - d_1\right) / \left(i - 1\right) \\ k_2 = \left(d_n - d_i\right) / \left(n - i\right) \end{cases} \tag{6}$$

Substituting Equation (6) into Equation (5) yields the expression shown in Equation (7).

$$\theta = \arctan \frac{\left|\left(d_i - d_1\right)\left(n - i\right) - \left(d_n - d_i\right)\left(i - 1\right)\right|}{\left(i - 1\right)\left(n - i\right) + \left(d_i - d_1\right)\left(d_n - d_i\right)} \tag{7}$$

Based on the above description, this study does not unconditionally accept labels from surrounding nodes in node propagation. Instead, it uses propagation strength to propagate more accurately. Additionally, *anklevalue* is used to automatically filter node labels during label filtering, avoiding the direct setting of filtering thresholds to prevent inappropriate threshold settings from affecting propagation results. The candidate group identification algorithm constructed in this study mainly consists of two parts. The first step is to initialize node labels: use the CD algorithm to initialize nodes and set nodes with close relationships to the same label. The second step is the judgment of candidate fake comment groups: based on the initial labels, iterate over the labels of each node, and finally obtain the label sets to which each node belongs. Labels with the same mark are considered a group, and users belonging to a single label are removed, as the goal is to identify groups. The core diagram-tag propagation false comment group detection algorithm (CD-TPFGD) process is shown in Figure 2.

3.2 Fusion of CD and metric weight measurement in CD-TPFGD

After obtaining a set of fake reviews, the task is to identify true fake review groups from the candidate set. True fake review groups refer to those groups of fake review publishers that actually exist and are organized to manipulate online reviews of a product or service by posting false reviews for the purpose of unfair competition. These groups typically share some common characteristics, such as similarity in review content, concentration of posting times, and unusual consistency in ratings. This study utilizes the Fake Review Group Index to rank the suspicion level of candidate groups, with higher-ranking groups being more likely to be fake [23]. Numerous scholars have developed various detection methods for fake reviews in existing research [24]. In this study, specific evaluation metrics, as shown in Figure 3, are selected based on the characteristics of fake review groups and the proposed model.

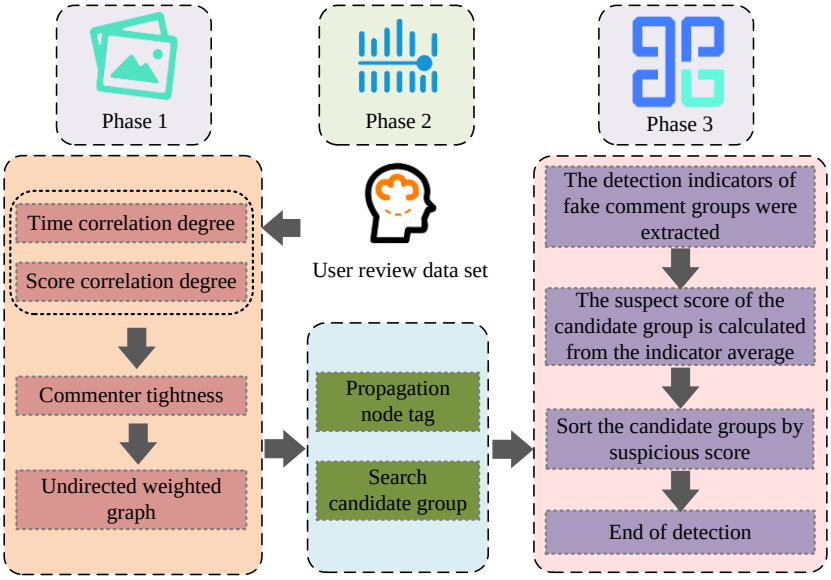


Figure 2: CD-TPFGD test flow

Evaluation index system	
Group nonchance	$L(g)=\frac{1}{1+e^{-(\lvert R_g\rvert+\lvert P_g\rvert-3)}}$
Intra-group review tightness	$RT(g)=\left[\lvert C_g\rvert/\left(\lvert R_g\rvert\lvert P_g\rvert\right)\right]L(g)$
Adjacency in a group	$RT(g)=2\times\sum_{a,b\in R_g}W(a,b)/\left[\lvert R_g\rvert\times\left(\lvert R_g\rvert-1\right)\right]L(g)$
Product tightness within the group	$PT(g)=\left\lvert\bigcap_{r\in R_g}P_r\right\rvert/\left\lvert\bigcup_{r\in R_g}P_r\right\rvert$
Mean time window	$TW(g)=avg_{p\in P_g}TW(g,p)\times L(g)\quad TW_p(g,p)=\begin{cases}1-SD_p/TT, & SD_p\le TT\\ 0, & SD_p>TT\end{cases}$
Score variance	$RV(g)=2\times\left(1-1/\left(1+e^{-avg_{p\in P_g}s^2(g,p)}\right)\right)L(g)$
Product evaluation rate	$RR(g)=\max_{p\in P_g}\left(\lvert R_{g_p}\rvert/\lvert R_p\rvert\right)$
Intra-group size	$GS(g)=1/\left(1+e^{-(\lvert R_g\rvert-3)}\right)$

Figure 3: Evaluation index system of fake reviews

All the metrics presented in Figure 3 are derived from the features of fake review groups. Among them, $L(g)$ denotes group non-contingency. $RT(g)$ denotes intra-group comment closeness. $NT(g)$ denotes intra-group neighbour closeness. $PT(g)$ denotes the product closeness within the group. $TW(g)$ denotes the mean time window. $RV(g)$ denotes the rating variance. $RR(g)$ denotes the product being rated rate. $GS(g)$ denotes the group size. R_g denotes a reviewer in cluster g. P_g denotes a reviewed product in cluster g. C_g denotes all reviews by reviewers in the cluster for the product in the group. P_r denotes a reviewer r reviewing the product. SD_p denotes the standard deviation in time of the reviews by reviewers in cluster g for the product p. TT denotes 30 d. $TW(g,p)$ denotes a time window for a single product. $S^2(g,p)$ denotes the variance of the ratings by reviewers in cluster g for the product p. R_p denotes the variance of the ratings by all reviewers in the dataset for the product p. R_{g_p} denotes all reviewers in cluster g who reviewed product p.

For a fake review group, it constitutes an organized and planned entity with a common purpose. Therefore, compared to general groups, there is greater cohesion among group members, similarity in the content of reviews, and similarity in the products being reviewed. This research considers seven indicators to calculate the final suspicion degree GSD of a group, as shown in Equation (8).

$$GSD = \left(RT(g)+NT(g)+PT(g)+TW(g)+RV(g)+RR(g)+GS(g)\right)/7 \quad (8)$$

Equation (8) represents the average of the seven detection indicators. Considering these seven features collectively, groups with higher values are considered more likely to be fake review groups. In previous studies, when detecting multiple fake review groups, researchers often use the mean value as the final suspicion level of the group without considering the differing importance of each indicator, which can affect the overall accuracy of the detection [25]. To better measure the weights of each indicator, this study proposes a metric weight measurement algorithm based on EM and AHP. EM is an objective weighting method based on information entropy, which evaluates the effectiveness of indicators by calculating the entropy value of each indicator. The higher the information entropy, the greater the information entropy of the indicator, the richer the amount of information it carries, and the greater the impact on decision-making. Therefore, the EM method can objectively reflect the importance of each indicator in detecting misjudgment. AHP is a subjective weighting method based on expert judgment, which determines the relative weight of each indicator by constructing a judgment matrix and calculating the consistency ratio. The AHP method can synthesize the subjective judgment of experts to complement the EM method, ensuring that both objectivity and subjectivity are taken into account when determining the weights. Based on EM and AHP, it can effectively combine objective data and experts' experience to improve the accuracy and reliability of misjudgment detection. In AHP, subjective judgment refers to an expert's assessment of the relative importance between indicators based on his or her understanding of the domain and the data. This judgment is subjective because it relies on the expert's experience and intuition. However, by using the EM results as a starting point, this subjective bias can be reduced because the EM results provide an objective basis based on data. It is assumed that there are n candidate fake review groups, each with (M) fake review group indicators. The normalization process for the indicators is represented as Equation (9).

$$z_{ij} = \frac{x_{ij} - \min\left(x_j\right)}{\max\left(x_j\right) - \min\left(x_j\right)} \quad (9)$$

In Equation (9), x_{ij} represents the value of the j-th indicator for the i-th group. x_j represents the score set of the j-th indicator across all groups. z_{ij} represents the normalized value of x_{ij}. These values are the basis for calculating the entropy values, which reflect the distribution of each indicator in the different pseudo rating groups. Normalization produces a dimensionless value that more intuitively reflects the importance of the indicator in the different dummy rating groups. The weight calculation for the j-th indicator under the i-th group is computed as shown in Equation (10).

$$r_{ij} = z_{ij} / \sum_{i=1}^{n} z_{ij} \quad (10)$$

In Equation (10), n represents the total number of candidate dummy assessment groups. The entropy calculation Equation for the j-th indicator is shown in Equation (11).

$$en_j = \left(-\sum_{i=1}^{n} r_{ij} \ln r_{ij}\right) / \ln n \quad (11)$$

The entropy value is calculated to measure the uniformity of the distribution of the values of each indicator. A larger entropy value indicates a more uniform distribution of the group's values on the indicator, and a smaller amount of information. Conversely, a smaller entropy value indicates a more concentrated distribution and a larger amount of information. The entropy weight calculation Equation for each indicator is presented in Equation (12).

$$ws_j = \left(1-en_j\right) / \sum_{j=1}^{s}\left(1-en_j\right) \quad (12)$$

The result of Equation (12) does not represent the final measurement of the importance of indicators. Rather, it serves as a preliminary calculation of the importance of each indicator. This calculation provides an objective basis for establishing the consistency matrix of the AHP. The information entropy weights obtained from the entropy weight method are then employed to facilitate a comparative analysis of various evaluation indicators. The weights are calculated to measure the informativeness of each indicator, i.e. the more informative the indicator, the lower its entropy value and the higher the corresponding weight. According to this study, indices with higher entropy weights are considered more important. Based on the comparative results, a consistency matrix is constructed, as shown in Equation (13).

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1s} \\ a_{21} & a_{22} & \cdots & a_{2s} \\ \vdots & \vdots & \ddots & \vdots \\ a_{s1} & a_{s2} & \cdots & a_{ss} \end{bmatrix} \quad (13)$$

In Equation (13), A represents the judgment matrix, and a_{ij} represents the result of comparing the importance of indicator i with indicator j. The construction of matrix A is based on the subjective assessment of the relative importance of the indicators by the experts. By constructing the judgment matrix, the weights of the indicators can be calculated, which in turn assesses their relative contribution to the detection of

misclassifications. In addition, the judgment matrix is used for consistency testing to ensure that the experts' judgments are consistent, thereby improving the reliability of the weight calculation. After constructing the judgment matrix, it is necessary to test whether the matrix is a consistency matrix. The consistency test coefficient is represented as shown in Equation (14).

$$CR = CI / RI \tag{14}$$

In Equation (14), CI represents the consistency index, and RI represents the random consistency index. CI is a measure of the consistency of the judgment matrix. It is calculated based on the difference between the largest eigenvalue of the judgment matrix and the size of the matrix, then divided by the size of the matrix minus one. The smaller the value of CI, the better the consistency of the judgment matrix, i.e., the more consistent the judgments of the experts are. RI is based on the average consistency index of a large number of randomly generated judgment matrices. The value of RI depends on the size of the judgment matrix. If $CR < 0.1$, it indicates that the matrix meets the standard. Otherwise, the judgment matrix needs to be reconstructed. The calculation Equation for group suspiciousness is shown in Equation (15).

$$sd_i = \sum_{j=1}^{s} x_{ij} B_j \tag{15}$$

In Equation (15), B_j represents the weight of the j th indicator. In the misperception test, different metrics have different weights. By multiplying the value of each metric by its weight, the contribution of each metric to the group suspicion can be determined. These contributions are added together to produce a composite measure, the group suspicion level, which reflects the overall performance of the group on all relevant indicators. This approach ensures that the more important metrics are given greater weight in the final assessment of the level of suspicion, thereby improving the accuracy and effectiveness of misclassification detection. In this study, the importance of indicators is first calculated using the EM. Then, based on this calculation, the weight vector is determined using the AHP. By integrating the EM and AHP, this research ultimately obtains the proportion of weights for each indicator. This method effectively addresses the objectivity issues of EM and the subjectivity issues of AHP. In summary, this study constructs a weighted user association graph, based on which the target group's candidate groups are identified using the label propagation algorithm. Subsequently, the entropy method-analytic hierarchy process (EM-AHP) algorithm is employed to measure the indicators and obtain a sorted list of groups. This results in the final algorithm for detecting fake review groups (CD-TPFGD-EM-AHP), and the system framework is illustrated in Figure 4.

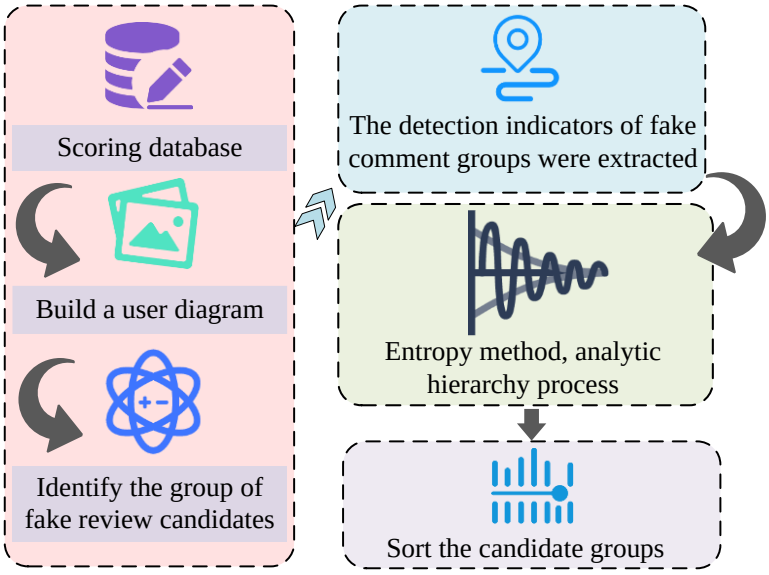


Figure 4: System framework of CD-TPFGD-EM-AHP

According to the process shown in Figure 4, CD-TPFGD-EM-AHP is able to demonstrate a clear superiority in terms of accuracy of false rating detection as well as running time. The method first constructs a user relationship graph, determines the similarity between users by analyzing their rating data and timestamps, and establishes links accordingly. Next, the user relationship graph is processed by applying the CD algorithm to identify a core group of users, which are grouped by iterative label propagation and community structure analysis. Then, EM-AHP is used to measure the weights of different indicators, where EM is used to objectively evaluate the information content of the indicators, and AHP adjusts the weights by combining the subjective

judgment of experts. Finally, these weighted indicators are combined to calculate the suspicion level of each user group, and based on the suspicion level ranking, the user groups most likely to be fake review groups are identified.

This process improves the accuracy and efficiency of fake review detection, providing e-commerce platforms with more effective tools to identify fake reviews.

4 Performance validation of fake review detection method based on CD-TPFGD-EM-AHP

The experiment initially delves into the discussion of parameters influencing CD-TPFGD-EM-AHP and compares the operational performance of CD-TPFGD-EM-AHP with CD-TPFGD. Subsequently, to better highlight the superior performance of CD-TPFGD-EM-AHP, the experiment introduces two other algorithms of the same type for comparative validation.

4.1 Impact of experimental parameters on the performance of CD-TPFGD-EM-AHP

To evaluate the algorithm proposed in this study, four labeled real-world datasets are used as experimental data-one from Amazon and three from Yelp. Amazon and Yelp are both well-known online shopping and review platforms where user reviews have a significant impact on consumers' purchase decisions. These datasets are well suited to illustrate the prevalence and complexity of the problem of fake reviews in the e-commerce domain. Furthermore, the selection of datasets from diverse platforms can enhance the generalizability of the experimental results. Amazon's primary focus is on merchandising, whereas Yelp specializes in local service reviews. This diversity in the datasets facilitates the evaluation of the algorithm's applicability in various scenarios. False online reviews not only violate business ethics, but also a variety of legal requirements, such as anti-unfair competition and consumer protection laws. The review content and rating behavior in these datasets are directly related to the scope of legal regulation and are therefore of high legal relevance. Experiments with these datasets can assess the effectiveness of algorithms in practical legal applications and provide technical support to e-commerce platforms in legal proceedings. Table 2 provides detailed statistics on the datasets. On this basis, the data are pre-processed by cleaning, text processing, score normalization, time erratic processing, and various density thresholds and time parameters are performed to determine the optimal parameters of the algorithm. The study is conducted using an Intel (TM) 7-3700 3.4GHz CPU and 8GB of RAM. The software is developed using Microsoft Windows 7 operating system and JDK1.8 development environment. Analysis tools such as SPSS and Eclipse 4.6.0 are also installed on the system. JDK 1.8 has good backward compatibility to support third-party libraries and frameworks used in the study, ensuring smooth transitions and fewer compatibility issues during development. A number of density thresholds are tested to determine the value that will best improve detection accuracy. Optimal parameter settings are selected by comparing performance at different thresholds. At the same time, the size of the time window is adjusted to assess changes in user behavior patterns over different time scales.

Figure 5 illustrates the accuracy versus Top-K for different α values for four different datasets (Amazon, YelpChi, YelpNYC, YelpZip). The red curves are the final choices of the experiments, which usually maintain higher accuracy in the Top-K region, especially when K is small. In this figure, the weight parameter has little effect on the algorithm in the Amazon database with a higher degree of association. The degree of association of the data at different thresholds reaches 0.9. In contrast, for Yelp data, which lacks such a close relationship, the impact is more significant. The density of a dataset is defined as the frequency of interactions between users and the degree of concentration of product reviews. Specifically, the density of a dataset can be measured by metrics such as the consistency of user ratings, the concentration of review time, and the frequency of interactions between users. Weighting parameters, on the other hand, are parameters used in the algorithm to adjust the impact of different features (e.g., user ratings, timestamps, etc.) on the final results. In denser datasets, such as the Amazon dataset, adjusting the weighting parameters has less impact on the algorithm's detection results due to the higher concentration of interactions between users and product reviews. This is because in high-density datasets, the consistency of user behavior is higher, allowing the algorithm to more consistently identify groups of false reviews and maintain a high

accuracy rate even when the weighting parameters are changed. In low-density datasets, such as the Yelp dataset, where interactions between users and product reviews are more dispersed, the adjustment of the weighting parameters has a greater impact on the algorithm's detection results. This is because in low-density datasets, the consistency of user behavior is lower, and the adjustment of the weighting parameters may affect the algorithm's identification of user behavior patterns and the detection of false review groups. Therefore, this suggests that the degree of influence of the weighting parameters on the dataset is closely related to the density of the dataset.

Table 2: Experimental data set

Data set	Comments (article)	Commenters (individual)	Product (unit)	Time frame
Amazon	53778	5051	17607	2016.04-2022.08
YelpChi	67396	38061	199	2011.10-2022.10
YelpNYC	359050	160223	921	2011.10-2022.01
YelpZip	608597	260275	5041	2011.10-2022.01

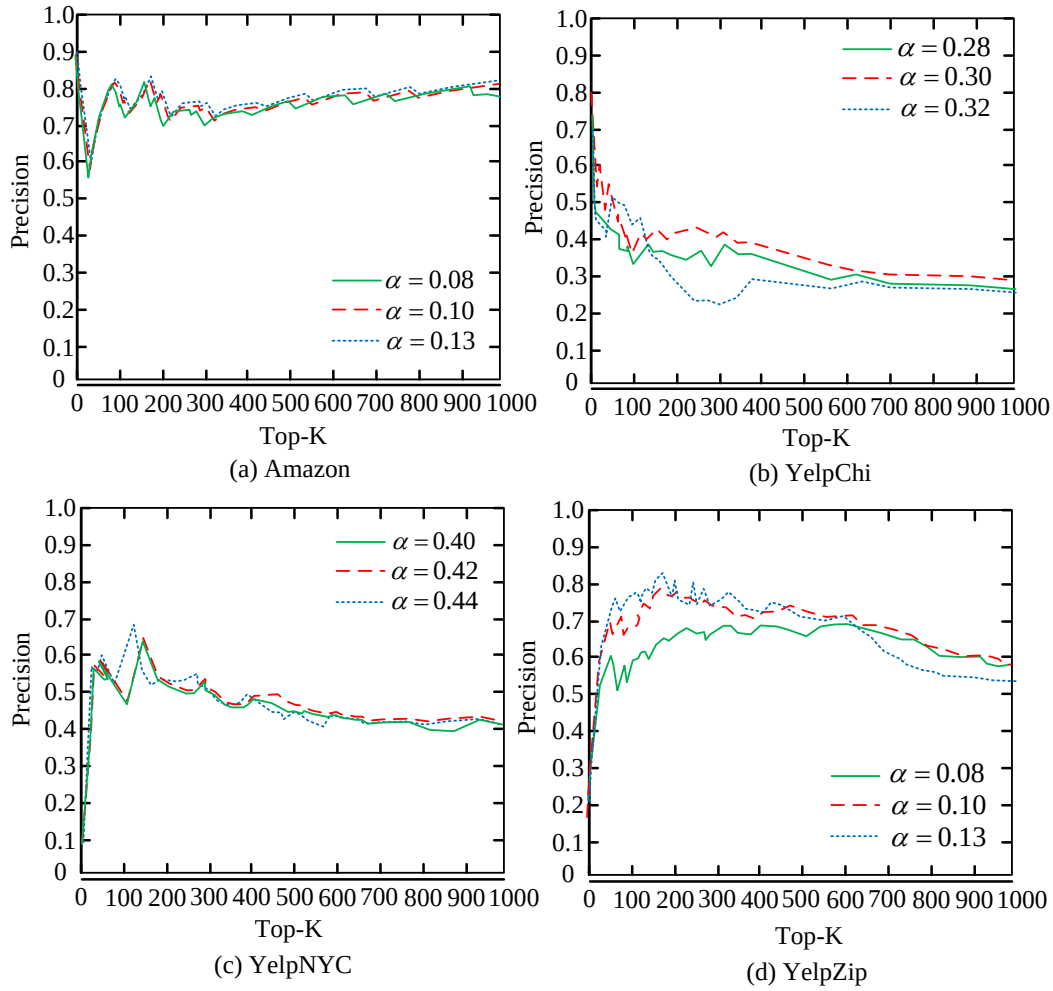


Figure 5: Influence of tightness thresholds of different values on test accuracy

As illustrated in Figure 6, the effect of varying time parameter values on test accuracy is evident for each dataset, with the legend denoting time intervals. The time interval is defined as the difference between the timestamp of a user's comment and the timestamp of the earliest or latest comment in the dataset. This time range is employed to analyze user behavior patterns over time. Similar to the weight parameters, the values corresponding to the red curve in this figure are the final results of this chapter. In this graph, unlike the weighted parameters, the time parameter has a minimal impact on test accuracy. For the YelpZip dataset, the effect of the

time parameter is more important for the top 300 reviewers. This may be due to the fact that the behavior of these reviewers is more concentrated and therefore the time parameter is better able to capture changes in this behavior. The influence of the time parameter decreases as the number of reviewers increases, which may be due to the fact that as the number of reviewers increases, the diversity of user behavior increases and the influence of the time parameter on the overall behavior patterns is relatively weaker.

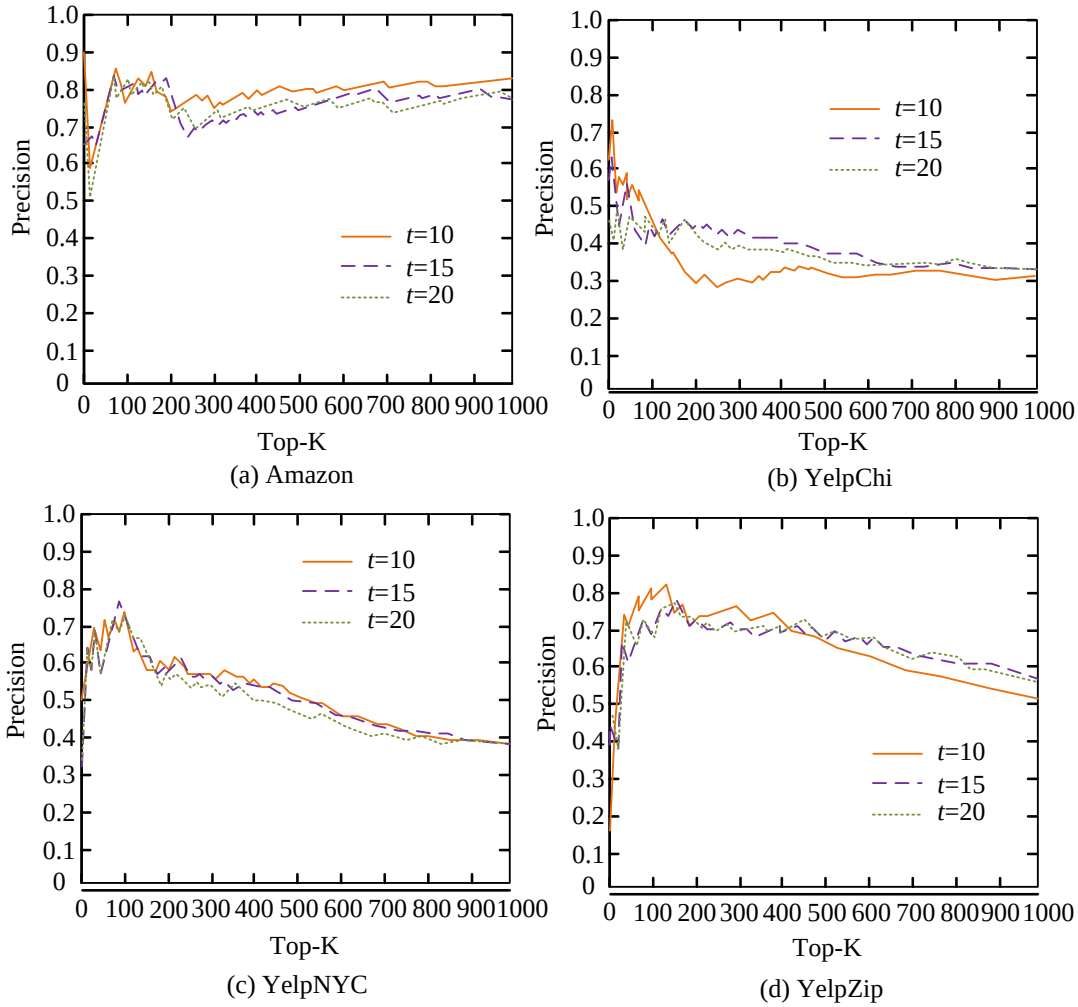


Figure 6: Influence of different time parameters of each data set on test accuracy

Table 3: The impact of label filtering on algorithm performance

Datasets	Enable tag filtering		Turn off tag filtering	
Amazon	Precision	0.88	Precision	0.78
	Recall	0.85	Recall	0.75
	F1 score	0.87	F1 score	0.76

Additionally, the study further analyzes the impact of label filtering *anklevalue* on algorithm performance. Using the Amazon dataset, the CD-TPFGD-EM-AHP algorithm is run with and without label filtering, and the recognition accuracy, recall rate, and F1 scores are recorded. As shown in Table 3, with label filtering enabled, there is a noticeable improvement in the accuracy, recall rate, and F1 scores of the algorithm. The accuracy increased from 0.78 to 0.88, the recall rate increased from 0.75 to 0.85, and the F1 score increased from 0.76 to 0.87. This indicates that label filtering effectively improves the detection performance of the algorithm.

On this basis, in order to validate the effectiveness of the CD-TPFGD-EM-AHP method in detecting false reviews in e-commerce, the detection accuracy of the two methods, CD-TPFGD and CD-TPFGD-EM-AHP, are first compared. The experiment selects the top 1000 users

for testing to validate the accuracy of the algorithm (Figure 7). The validation results of the CD-TPFGD algorithm outperform the CD-TPFGD-EM-AHP algorithm for the Amazon dataset with Top-K of 50-52 segments, the YelpNYC dataset with Top-K of 80-110 segments, and the YelpZip dataset with Top-K of 390-450 segments, indicating that there may be a misclassified cluster where the test precision is low. Overall, the CD-TPFGD-EM-AHP algorithm gives better results.

4.2 The performance comparison verification of the fake comment detection model based on CD-TPFGD-EM-AHP

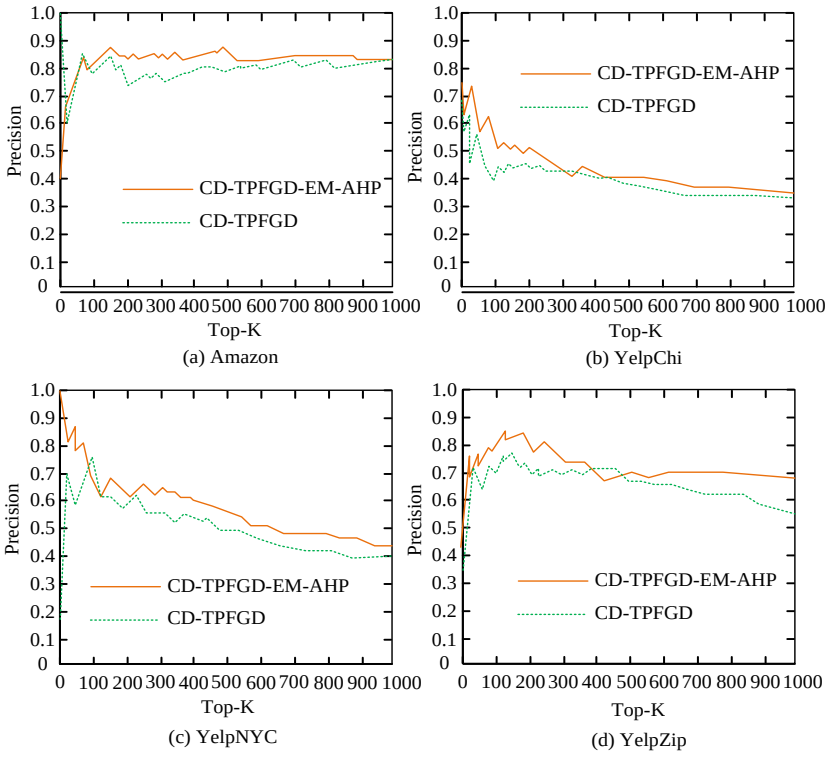


Figure 7: Difference in detection accuracy between CD-TPFGD and CD-TPFGD-EM-AHP

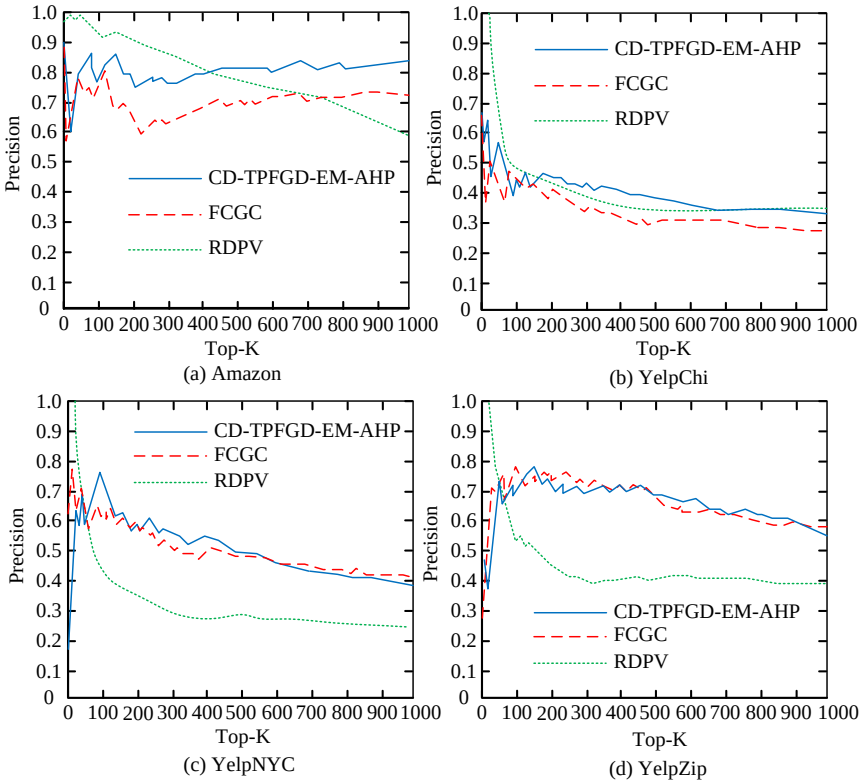


Figure 8: Test accuracy results of three methods on four different data sets

To comprehensively assess the performance of the CD-TPFGD-EM-AHP method and demonstrate its potential in practical applications, the study further selected two currently popular false comment detection methods for comparative analyses. This is done to more clearly demonstrate the advantages of the CD-TPFGD-EM-AHP method in terms of accuracy, efficiency, and applicability. These methods are the found fake comment groups in graph clustering (FCGC) and the user ranking method based on doubtful probability values (RDPV). The accuracy of these three methods on four different datasets is illustrated in Figure 8. The CD-TPFGD-EM-AHP method has been demonstrated to exhibit consistent and reliable performance across various datasets. This finding suggests that the CD-TPFGD-EM-AHP method can be effectively applied to multiple datasets and can achieve effective fake comment detection on these datasets. On the Amazon, YelpNYC, and YelpZip datasets, the CD-TPFGD-EM-AHP method showed better detection and accuracy, with accuracies of about 0.88, 0.42, and 0.71, respectively. It suggests that the CD-TPFGD-EM-AHP method has a high degree of stability and applicability on these datasets. However, on the YelpChi dataset, CD-TPFGD-EM-AHP is slightly less accurate than RDPV, with an accuracy of about 0.31, while RDPV performs slightly better on this dataset. This difference may be due to the unique characteristics of the YelpChi dataset. Overall, the CD-TPFGD-EM-AHP method showed better detection and accuracy on the Amazon, YelpNYC, and YelpZip datasets.

Figure 9 illustrates the recall of the three methods on the four datasets. On the YelpChi dataset, the recall of CD-TPFGD-EM-AHP is slightly lower than that of RDPV, which is consistent with the trend of accuracy observed in Figure 8. On the YelpZip dataset, CD-TPFGD-EM-AHP has a recall comparable to that of RDPV in most cases, but lower than RDPV at some points. On the other datasets, CD-TPFGD-EM-AHP has a high recall, suggesting that it is able to efficiently identify fake reviews in most cases.

Figure 10 illustrates the F1 scores of the three methods across four datasets. Through an analysis of these four datasets, it is observed that CD-TPFGD-EM-AHP outperforms RDPV and its effectiveness gradually increases with an increase in the number of viewers. RDPV performed poorly, especially on the YelpNYC dataset. The F1 score of CD-TPFGD-EM-AHP is superior to FCGC, but slightly lower compares to RDPV. Overall, CD-TPFGD-EM-AHP exhibits higher F1 scores compared to other methods in detecting false comment groups. The CD-TPFGD-EM-AHP algorithm does not perform as well on the YelpChi dataset as it does on other datasets. This may be due to the unique characteristics of the YelpChi dataset. YelpChi mainly contains reviews of localized services, which may differ significantly from

the other datasets in terms of language style and review content. The reviews in YelpChi contain more local expressions and slang, which affects the effectiveness of the algorithm's feature extraction based on linguistic patterns.

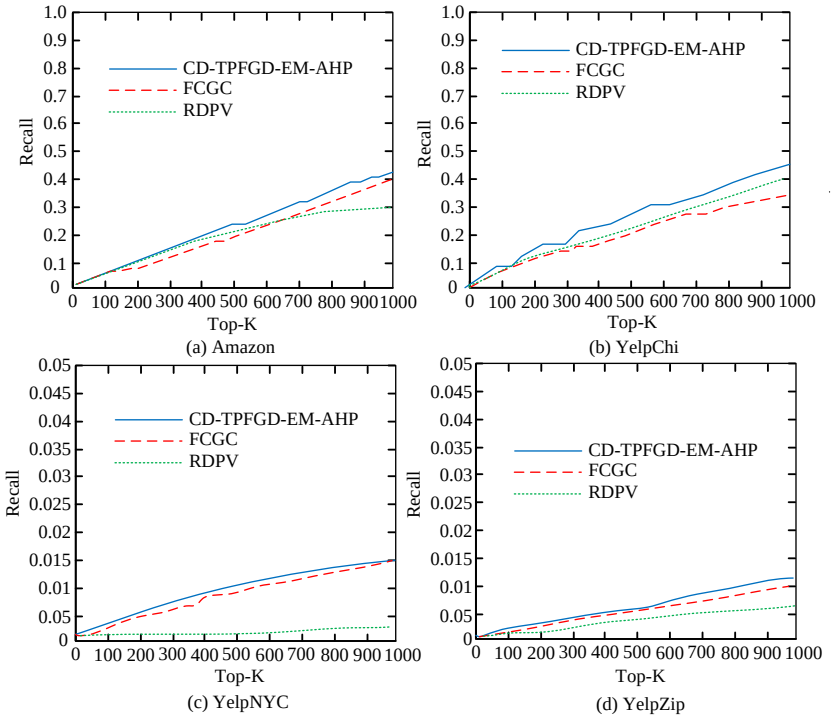


Figure 9: Recall rates of the three methods on the four data sets

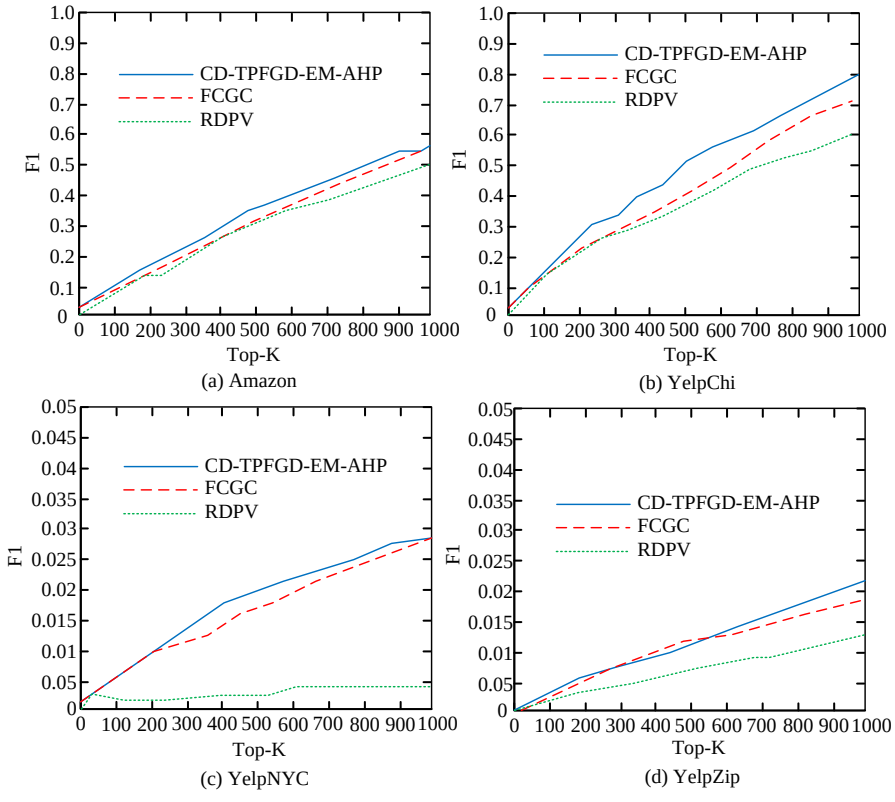


Figure 10: F1 values for three methods on four datasets

Table 4 presents a comparison of the running time of the three algorithms on four different datasets. The arithmetic mean of the 10 experimental running times is calculated to ensure the reliability of the results and to minimize the effect of random errors. This is due to the RDPV algorithm's inherent randomness in processing data, which can lead to variability in outcomes across iterations. To obtain a stable and reliable performance metric, 10 experiments are repeated, and the average running time of these experiments is calculated. The table indicates that CD-TPFGD-EM-AHP shows a significant advantage in computational speed compared to the RDPV algorithm. On the YelpChi dataset, the computational time for CD-TPFGD-EM-AHP is longer than that of FCGC, reaching 142.11 seconds. However, CD-TPFGD-EM-AHP demonstrates lower computational time and better results when dealing with other types of data. Furthermore, an analysis of the relationship between the sample sizes of the four datasets and the running time of the algorithms reveals a direct correlation between the increase in the speed of the CD-TPFGD-EM-AHP operation and the increase in the sample sizes. This correlation stands in contrast to the performance of algorithms such as FCGC and RDPV. Therefore, CD-TPFGD-EM-AHP has minimal impact on computational speed, indicating better identification effectiveness compared to FCGC, RDPV, and similar methods.

Table 4: The results of running time comparison of 3 algorithms on 4 data sets

Data set	CD-TPFGD-EM-AHP	FCGC	RDPV
Amazon	28.12s	42.03s	3601.11s
YelpChi	142.11s	85.99s	301.45s
YelpNYC	41.11s	1201.56s	24001.11s
YelpZip	164.12s	1419.11s	48021.01s

Note: Running time is one of the key metrics for measuring the usefulness of an algorithm. Although accuracy is the core criterion for evaluating the performance of an algorithm, the running time of an algorithm is also crucial in practical applications, especially when dealing with large datasets. An algorithm, even with high accuracy, may fail to deliver results in a reasonable amount of time if the running time is too long, limiting its use in real-time or large-scale application scenarios.

Table 5: Comparison of baseline models

Data sets	SVM	RF	LSTM	CD-TPFGD-EM-AHP	P-value
Amazon	0.82	0.83	0.83	0.88	0.00
YelpChi	0.77	0.79	0.75	0.79	0.03
YelpNYC	0.73	0.76	0.71	0.83	0.00
YelpZip	0.67	0.70	0.65	0.75	0.00

Finally, in order to further confirm the effectiveness of the proposed method, the study introduces three baseline models, SVM, RF, and LSTM, to compare the performance with the proposed method. The details are shown in Table 5.

In Table 5, the detection accuracy of the proposed CD-TPFGD-EM-AHP in this study is significantly higher than that of the three baseline models, SVM, RF and LSTM, for the four dataset types ($P<0.05$). This indicates that the use of CD in combination with indicator weighting metrics is reasonable and superior for the detection of misclassification. It also indicates the positive effectiveness of the proposed improvement strategy of the study.

5 Discussion

The CD-TPFGD-EM-AHP method proposed in the study demonstrated superior detection performance on the Amazon, YelpChi, YelpNYC, and YelpZip datasets compared to methods such as RDPV, FCGC, SVM, RF, and LSTM. By integrating label propagation based on CD with metric weight measurement using EM and AHP, this method could more accurately identify user relationships and review patterns, improving the accuracy of fake review detection. The CNN+LSTM method presented in reference [12] exceled at capturing sequential patterns, but had limitations in simulating complex user interactions and the subtleties of review context, making it difficult to distinguish between real and fake reviews. The n-gram-based system in reference [13] was effective

for text classification tasks, but struggled with the nuances of detecting carefully crafted fake reviews.

The high recall rate in YelpZip indicated that the CD-TPFGD-EM-AHP effectively captured dense relationships in review data, but could face challenges in sparsely connected datasets. This was due to the algorithm's reliance on user interaction density and review consistency, which were less common in sparse datasets. In dense datasets like YelpZip, where user interactions and review patterns were more frequent and consistent, the proposed method could more accurately identify fake review groups. Future work will focus on improving the robustness of the model in such scenarios by integrating alternative data sources or developing hybrid models that can adapt to different data densities.

In terms of algorithm parameter selection, the weight parameter adjusted the impact of different features on the final results, having a smaller impact on dense datasets like Amazon, but a larger impact on sparse datasets like Yelp. The time parameter, which represented the timestamp difference between user reviews, had a small impact on the overall accuracy of the test, but was more important for capturing behavioral patterns in certain datasets. These results underscored the importance of carefully tuning parameters based on specific dataset characteristics. High accuracy ensured the reliability of the model's detection results, and precision indicated the proportion of identified fake reviews that were actually false. Together, these metrics affected the credibility of reviews presented to consumers and the reputational and financial impact on merchants and e-commerce platforms. However, while the model provided a good balance, improving the sensitivity of fake review detection without sacrificing the model's sensitivity may require more computational resources. The model needed further testing on a wider range of datasets to confirm its broad applicability. The model could struggle with reviews that closely mimic real user language, or when faced with new fake review strategies, and further optimization of error case review is needed.

6 Conclusion

In the present day, numerous unscrupulous e-commerce entities employ a large number of fake accounts to publish misleading reviews, attempting to boost their profits through this method. This violates commercial laws and harms consumer interests. To enhance the detection of fake reviews, this study proposed an e-commerce fake review detection method based on CD and metric weight measurement. The performance of the proposed model was validated in this study, and the experimental results indicated that the impact of weighted parameters on the dataset was related to the dataset's density. The detection accuracy of CD-TPFGD-EM-AHP surpassed that of CD-TPFGD. This study compared CD-TPFGD-EM-AHP with two other methods, FCGC and RDPV. The results demonstrated that CD-TPFGD-EM-AHP achieved detection accuracy of approximately 0.88, 0.31, 0.42, and 0.71 for the Amazon, YelpChi, YelpNYC, and YelpZip datasets, respectively, with stable detection outcomes. The recall and F1 score results for the three methods indicated that CD-TPFGD-EM-AHP exhibited superior performance compared to FCGC and RDPV. Additionally, the running time of CD-TPFGD-EM-AHP on the four datasets is better than the other two methods, with the shortest running time being 28.12 seconds. The limitation of this study lies in its failure to discuss sparse datasets using the proposed model, which could be considered as a direction for future research.

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An Efficient Two-State Feature Attention-Based GRU for Text Classification

Dhurgham Ali Mohammed[1,2], Kalyani A. Patel[3]
[1]Faculty of Computer Science, Gujarat University, Ahmedabad, India
[2]Department of Computer Science, Faculty of Education for Girl, University of Kufa, Iraq
[3]K.S. School of Business Management and Information Technology, Gujarat University
E-mail: dhurghama.alhasani@uokufa.edu.iq, kalyanipatel@gujaratuniversity.ac.in

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Text classification has become crucial for mechanically sorting documents into specific categories. The goal of classification is to assign a predefined group or class to an instance based on its characteristics. To attain precise text categorization, a feature selection scheme is employed to categorize significant features and eliminate irrelevant, undesirable, and noisy ones, thereby reducing the dimensionality of the feature space. Many advanced deep learning algorithms have been developed to handle text classification drawbacks. Recurrent neural networks (RNNs) are broadly employed in text classification tasks. In this paper, we referred to a novel Two-state GRU based on a Feature Attention strategy, known as Two-State Feature Attention GRU (TS-FA-GRU). The proposed framework identifies and categorizes word polarity through consecutive mechanisms and word-feature capture. Furthermore, the developed study incorporates a pre-feature attention TS-FA-GRU to capture essential features at an early stage, followed by a post-feature attention GRU that mimics the decoder's function to refine the extracted features. To enhance computational performance, the reset gate in the ordinary GRU is replaced with an update gate, which helps to reduce redundancy and complexity. The effectiveness of the developed model was tested on five benchmark text datasets and compared with five well-established traditional text classification methods. The proposed TS-FA-GRU model demonstrated superior performance over several traditional approaches regarding convergence rate and accuracy. Experimental outcomes revealed that the TS-FA-GRU model achieved excellent text classification accuracies of 93.86%, 92.69%, 94.73%, 92.46%, and 88.23 on the 20NG, R21578, AG News, IMDB, and Amazon review dataset respectively. Moreover, the results indicated that the proposed model effectively minimized the loss function and captured long-term dependencies, leading to exceptional outcomes when compared to the traditional approaches

Povzetek: Predstavljen je nov model za klasifikacijo besedil, imenovan Two-State Feature Attention GRU (TS-FA-GRU), ki temelji na strategiji pozornosti na značilke. Model izboljšuje standardni GRU z zamenjavo reset vrat z posodobitvenimi vrati in uporabo pred- in po-pozornosti za izboljšanje ekstrakcije značilk.

1 Introduction

With the rapid advancements in computer technology and the internet, a tremendous amount of digital textual data is generated daily. Efficiently and precisely retrieving specific content from this vast information pool has become a common challenge [1]. Textual data is highly dimensional, often containing irrelevant and redundant features that are problematic to manage. The issue of data overload was first identified in the early 1960s. Today, a substantial portion of online information exists as structured and unstructured text, with managing the latter posing an essential issue for large organizations [2]. Machine learning delivers a solution by automatically analyzing data, identifying patterns, and making classifications with minimal human intervention. Extracting valuable information relevant to specific interests from a continuously growing pool of documents has become a critical task in machine learning [3]. This necessitates the use of well-organized classification methods capable of assigning texts to one or more classes (labels). These methods have been effectively utilized in many Natural Language Processing (NLP) applications, including sentence classification [4], topic modeling and text clustering [5], spam detection [6], website categorization [7], disease report identification [8], and document summarization [9]. Text classification using RNNs influences the network's capability to process sequences data, making it particularly effective for tasks connecting textual information. RNNs, and their more progressive variants like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), are designed to hold information from previous steps in the sequence, allowing them to understand context and dependencies in text [10, 11]. This capability is crucial for tasks such as sentence analysis, language translation, and spam detection, where the meaning of a word often depends on its context within a sentence or document. In recent years,

the rapid increase in text data has made NLP a fascinating area for deep learning tasks. Figure 1 outlines the key steps of NLP, which are utilized across numerous NLP applications. The use of RNNs in text categorization has led to important developments in NLP, making it possible to develop more sophisticated and precise models for understanding and organizing textual data [12].

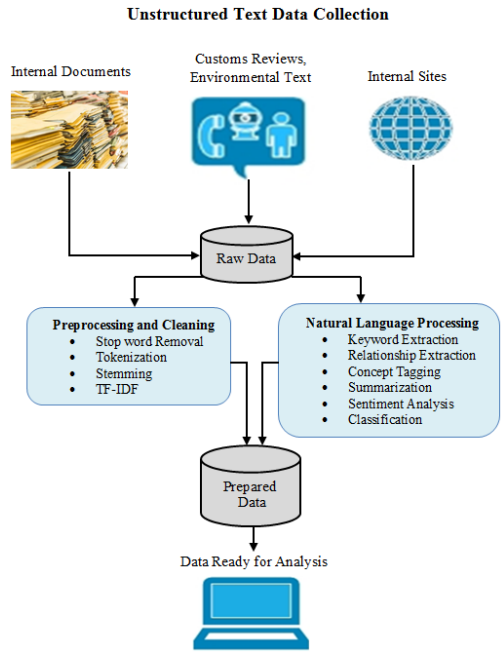


Figure 1: Text classification steps

In recent years, RNNs have been extensively applied in several data mining applications, demonstrating superior performance in classification tasks [13]. RNNs provide excellent semantic composition procedures for text categorization and can capture sequential dependencies in progressive data. There are two main types of RNNs: LSTM networks and GRUs. Text data is high-dimensional with numerous features, making extracting informative features from raw data with a single layer challenging. Therefore, recent deep learning research has focused on utilizing multiple layers to extract highly informative features. Among RNNs, GRUs have shown particular promise in addressing various text classification problems. While previous research has explored the accuracy and performance of GRUs for text classification, certain drawbacks remain in the standard GRU model that require further improvement. Lee et al. [14] established the Word2Vec word embedding technique, which converts each word into a sparse vector corresponding to specific terms, distributing various semantic and syntactic features across each dimension in vector space. Zulqarnain et al. [15] introduced an effective GRU network-based word embedding strategy for sentence classification, which utilized the word2vec technique. Soni et al. [16] utilized Convolutional Neural Networks (CNNs) for sentence modeling, achieving superior text classification results by using ConvoNet methodology to competently categorize sentiment polarity based on the skip-gram method from different positions in a sentence. However, CNNs focus on local features and exclude sequence information, which excels in progressive correlations amongst context and sentiment words through a useful gating mechanism [17]. Despite this, RNNs are still subject to the vanishing gradient and exploding gradient deficiencies [18]. Several deep learning methodologies have been introduced to address these drawbacks, including LSTM [19] and GRU [20]. GRU, an advanced version of LSTM, has been widely employed in numerous NLP applications due to its more effective computational process while retaining the benefits of LSTM. In this study, we examine the effectiveness of the conventional GRU for text classification employing distributed representation on a social platform. The GRU network's capability to tackle the vanishing gradient and exploding gradient issues in typical RNNs is one of its key strengths. We conducted experiments on five benchmark datasets: 20newsgroup (20NG), Reuters21578 (R21578), AG's News, IMDB, and Amazon reviews. Our research aims to improve the typical GRU structure by integrating a Two-State Feature Attention GRU (TS-FA-GRU) model. This model employs an attention mechanism to identify and utilize the most informative features for text classification. The key goal of our study is to boost text classification accuracy while minimizing information loss within the GRU framework. The key contributions of this research are included as follows:

- Introduced a novel the Two-State Feature Attention GRU (TS-FA-GRU) architecture to tackle text classification challenges. This architecture utilizes a feature attention strategy to extract informative features.
- Employed the extensively used unsupervised word embedding technique, GloVe, for vector initialization.
- This study evaluates the impact of replacing the reset gate with an update gate in the candidate state of the traditional GRU network, similar to the approach by Zhou (2016), which finds the absence of the reset gate does not substantially impact on model performance.
- Our contribution focused on developing a mechanism that provides efficient computation and robust performance with fewer parameters.
- This study demonstrates through experimental results that the developed TS-FA-GRU framework performs effectively across benchmark datasets such as 20NG, R21578, AG's News, IMDB, and Amazon review, highlighting its ability to capture long-term dependencies and achieve superior results with significantly lower computational costs compared to traditional approaches.

2 Recent review of text classification

Text classification, an essential task in NLP, has seen substantial developments with the advent of deep learning approaches. This review explores recent developments and innovations in text categorization employing deep learning models [21]. RNNs and their variants, mainly LSTM networks, have been extensively utilized for text classification due to their capability to extract sequential dependencies [22][22]. Singh et al. [23] introduced the Hierarchical Attention Network (HAN) for document categorization, which exploits a hierarchical structure and attention mechanism to emphasis on important words and sentences, achieving state-of-the-art results on numerous benchmarks. Cunha et al. [24] referred to the Transformer language model, which depends completely on self-attention mechanisms to capture long-range dependencies, overcoming the deficiencies of RNNs. BERT (Bidirectional Encoder Representations from Transformers), introduced by Nissa et al. [25], further progressive the arena by utilizing a pre-training method on large corpora and fine-tuning the exact tasks, attaining superior performance across various benchmarks. Gu et al. [26] introduced TextGCN, which constructs a document-word graph and influences GNNs to learn embeddings for text classification, representing substantial enhancements over traditional methods. Recent research has also examined hybrid approaches that combine the strengths of various architectures. For example, Ashraf et al. [27] presented a hybrid approach integrating CNNs and RNNs, leveraging CNNs for capturing local patterns and RNNs for sequential dependencies, achieving notable improvements in classification accuracy. Another hybrid model by Wang et al. [28] combined BERT with Graph Neural Networks to utilize both contextual and relational information, resulting in state-of-the-art performance on different datasets. Conventional RNNs are comprised of fully connected layers that process transitions from the input layer to the hidden layer, and from the hidden layer to the output layer through recurrent connections, as illustrated in Figure 2. Pandian et al. [29] described a three-layer structure enhanced with a "context unit" set, where the connections among hidden layer nodes and context layer nodes have fixed weights. RNNs, being a form of deep neural network tailored for sequential data, are known for their high expressiveness [30].

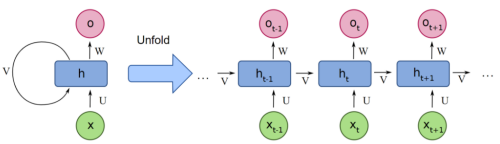


Figure 2: Traditional RNN [31]

RNNs maintain a vector of initiations for each time step, classifying them as a type of DNN. The decision made by an RNN at time step $t-1$ influences the decision at time step t. Therefore, an RNN has two sources of input: the current time step and the preceding one, which determines its response to new data. While standard RNNs can learn patterns in sequential time series data, they are susceptible to the vanishing gradient problem, which affects performance [32]. Despite being powerful for handling sequential data, RNNs are challenging to learn with gradient descent due to the vanishing and exploding gradient issues [33]. These problems are mitigated by advanced variants of standard RNNs, such as LSTM and GRU. GRUs, in particular, have fewer parameters than LSTMs, reducing the risk of overfitting and saving training time. Assumed consecutive input of word vectors (X1, X2, X3...XT), produces a corresponding sequence of hidden states (h1, h2, h3...hT), which is computed at time step t. The output at each step can then be determined using the following RNN calculation:

$$O_t = \varphi(W_x x_t + U_o h_{t-1}) \tag{1}$$

$$H_t^l = \varphi(W_x h_{t-1}^l + U_H h_{t-1}^l) \tag{2}$$

where is the recurrent weights matrix, is the input to-hidden weights matrix, and φ represents an arbitrary activation function. Equations 1 and 2 depict the activity of the hidden layer as influenced by its prior state. In contrast, the GRU, a more efficient and improved version of the LSTM, was initially introduced by Chung et al. [17] for arithmetical machine learning. The GRU, inspired by the LSTM, facilitates information flow within the unit via an update gate z_t and a reset gate r_t, without requiring a distinct memory component [34].

Consequently, the GRU excels in capturing the mapping relationships in time series information whereas giving assistance including minimize complexity and more efficient computation. Figure 3 depicts the structure of the GRU, highlighting the interactions between the update and reset gates.

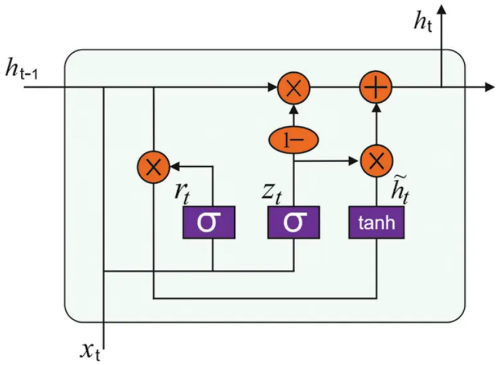


Figure 3: Traditional GRU structure [35]

Like the LSTM, the GRU uses the gating mechanism to regulate the flow of information within the unit, eliminating the need for separate memory cells. The GRU manages and filters information using its internal memory by combining the input and forget gates into a single update gate, which

integrates the previous activation $h_(t-1)$ and the candidate's state h_t. The GRU's three primary components are the update gate, reset gate, and candidate state. The equations governing these mechanisms are presented in equations (3 to 6):

$$z_t = \varphi(V_x z x_t + U_h z h_(t-1) + B_z) \tag{3}$$

$$r_t = \varphi(V_x r x_t + U_h r h_(t-1) + B_r) \tag{4}$$

$$\tilde{h}_t = \tanh(V_{xh\tilde{h}} x_t + U_{hh\tilde{h}}(r_t \cdot h_{t-1}) + B_{\tilde{h}}) \tag{5}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \tag{6}$$

The weight matrices between the input layer and the update gate, the reset gate and the candidate state are indicated as $V_x z$,$V_x r$ and $V_(x\tilde{h})$, respectively, while the recurrent connection weight matrices are indicated by $U_h z$, $U_h r$ and $U_(h\tilde{h})$ respectively. The input sample at time t is represented by x_t, and the hidden state output is denoted as h_t. The sigmoid activation function for the update and reset gates is symbolized by φ, with element-wise multiplication executed by *. The biases corresponding to the update gate, reset gate, and candidate state are illustrated by B_z, B_r and $B_(\tilde{h})$.

Table 1 illustrates the comparison review of various deep learning approaches integrating attention mechanisms for text classification, each model evaluated on datasets such as 20 Newsgroups, Reuters-21578, AG's News, IMDB, and Amazon Reviews, and highlights the model's findings, strengths, and limitations.

3 The proposed framework

In this study, we detail the specific components of the developed architecture, which comprises a two-state GRU based on feature attention strategy GRU, a newly developed model namely, Two-State Feature Attention (TS-FA-GRU). Furthermore, this research investigates the effects of substituting the reset gate r_t with an update gate z_t in the candidate state $\tilde{h}_t$ of traditional GRU design. Consistent with the findings of Zhou et al., [41], our results indicate that the absence of the reset gate does not substantially impact model performance. The established framework utilizes word embeddings as inputs, which are used to extract high-level contextual word features over time steps. The embedding layer predicts these features, then passes them to the two state GRU language mechanism, and ultimately classifies them using a softmax classifier. The primary contribution of the proposed mechanism is its ability to extract crucial features through two main phases: Pre-Feature Attention TS-GRU and Post-Feature Attention TS-GRU.

3.1 Embedding layer

The embedding layer plays a crucial role in developing networks for text classification. The initial step in this process is pre-processing, which entails cleaning the text data. To convert each word in the sentences into a real-valued vector, we employed the pre-trained 300-dimensional GloVe method. These pre-trained vectors adeptly extract both semantic and syntactic information, making them essential for text categorization by transforming word contexts into real-valued feature vectors. Let $L \in R^{V*d}$ determine the embedding inquiry table generated by GloVe, where d is the dimensionality of the words and the vocabulary size denoted by V. Consider a serial of input containing n words and the sentiment resource containing m words. The sequential inputs of the text contexts extract word vectors from L, producing a list of vectors $[W_1, W_2 \ldots, W_n]$ where each $W_i \in R^d$ is the word vector for the corresponding word. Likewise, the sentiment resource sequence extracts word vectors, producing a list $[W^s{}_1, W^s{}_2, \ldots, W^s{}_m]$. This process enables the creation of a matrix for context words and a matrix $W^c = [W_1, W_2 \ldots, W_n] \in R^{n*d}$ for text classification resource words. This approach allows for the establishment of word-level connections between sentiment words and context words, formatted as a correlation matrix, as illustrated in. Essentially, this process combines all word embeddings within V.

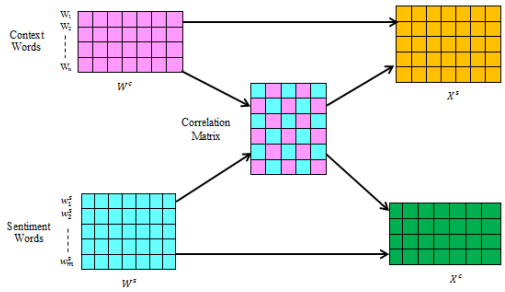


Figure 4: Sentiment-context word correlation

Build _vocab : This function takes the Harvard IV-4 dictionary and text data as input. It outputs a word_frequency array, which includes each word's unique identifier and its frequency in the dataset. Text categorization values range from 0 to 1, where 0 refers to negative analysis, while 1 refers to positive analysis. Words with higher sentiment values have higher word frequency values.

Build_co-occur: This function accepts the word_frequency array and selected text data as inputs, along with parameters for the context window size and minimum count, which are set to 10. The context window size determines how many words are considered to represent the context of each word, and the least count is used to filter out infrequent word cooccurrence pairs. The function determines the range from context_word_id to m_word by counting the words in between. It then generates a sparse matrix containing co-occurrence tuples in the format (word_id, context_word_id, xij), where

Table 1: Comparison summary of various deep learning approaches

Previous Studies	Approaches	Findings	Strengths	Limitations
Singh et al. [23]	HAN+Attention Mechanism	Outperformed SOTA approaches in document classification tasks.	Methods documents hierarchically, capturing word and sentence importance.	Complex architecture; requires large datasets for optimal performance.
Ashraf et al. [27]	CNN+RNN	Achieved strong performance by combining CNN for local feature extraction and RNN for capturing sequential patterns.	Captures both local and sequential dependencies effectively.	Increased computational cost and potential over fitting with small datasets.
Nissa et al. [25]	CNN-XGBoost	Obtained SOTA results in different text classification benchmarks.	Handles long-range dependencies and allows for effective parallelization.	Requires extensive computational power and large datasets; may over fit on small datasets.
Wang et al. [28]	BERT + Text FGC	Fine-tuned BERT with Feature Guided Context (FGC) showed significant improvement in text classification tasks, leveraging contextual embeddings.	Provides rich contextual embeddings; achieves state-of-the-art performance on diverse datasets.	Requires large computational resources and extensive training data.
Yao, [36]	Attention-Based BiLSTM	Reported significant enhancement in sentiment analysis tasks.	Captures long-term dependencies and focuses on important words in the text.	Computationally intensive; over fit with limited data.
Liu et al. [37]	CNN with Attention Mechanism	Improved performance in capturing local features for text classification tasks.	Excels at capturing local features and focuses on relevant parts of the text.	They may struggle with capturing long-term dependencies and are sensitive to hyper parameter settings.
Ma et al. [38]	CNN+ Bi-GRU	Combined CNN with Bi-GRU for sequential patterns, improving accuracy and robustness on multiple datasets.	Balances local and bidirectional sequential feature extraction.	Higher complexity individual CNN or RNN models;require careful hyper parameter tuning.
Salini et al. [39]	CNN+ Bi-GRU + Multi Attention Mechanism	Enhanced classification accuracy by incorporating multi-attention mechanisms, allowing the model to dynamically focus on crucial parts of the text.	Integrates multi-attention to prioritize significant features, improving interpret ability and performance.	Increased model complexity and computational demand; risk of over fitting with small datasets.
Guo et al. [40]	Hybrid Models (CNN-RNN-Attention)	Achieved improved accuracy by combining multiple neural network architectures.	Combines strengths of CNNs and RNNs with attention to captured both local and global features.	Increased model complexity; higher computational cost; and potential over fitting with small datasets.

xij represents the co-occurrence value. Figures 5 and 6 demonstrate the flow diagrams for the Build_vocab and Build_cooccur functions, respectively.

Train_GloVe: This function initializes the network parameters and accomplishes the training process. Its usages the co-occurrence data to update the biases and weight vectors during each iteration.

3.2 Removing the reset gate

In the computational framework, the reset and update gates utilize parallel parameters, differing only slightly in their values. The reset gate refers to some complexity and redundancy when interacting with the update gate and candidate state in the GRU model. To address this issue, the proposed approach removes the reset gate r_t from the standard GRU architecture and replaces it with the update gate z_t in the candidate state $\hat{h}_t$. This modification reduces model execution time without significantly affecting accuracy. Consequently, the equations governing the GRU are adjusted as

follows in place of Equations (7) and (8):

Update gate

$$z_t = \varphi(W_{xz}x_t) + U_{hz}(h_{t-1}) + b_z \tag{7}$$

Candidate state

$$\hat{h}_t = \tanh(W_{x\hat{h}}x_t) + U_{h\hat{h}}(r_t \cdot h_{t-1}) + b_{\hat{h}} \tag{8}$$

In this context, the candidate state is denoted by $\hat{h}_t$, with W and b representing the weight and bias respectively. Here, x_t signifies the input, and $h_(t-1)$ indicates the previous time step. By substituting the update gate z_t for the reset gate r_t in the candidate state $\hat{h}_t$, Equation (8) is transformed into Equation (9):

$$\hat{h}_t = \tanh(W_{x\hat{h}}x_t) + U_{h\hat{h}}(z_t \cdot h_{t-1}) + b_{\hat{h}} \tag{9}$$

where z_t is the update gate that replaces the reset gate r_t, and the standard equation for z_t is provided in Equation (23). Additionally, this research substitutes the hyperbolic tangent activation function (tanh) with the Rectified Linear Unit (ReLU) activation function in the candidate state, resulting in the modification of Equation (9) to Equation (10). The contributions are highlighted in red. "In this modification, z_t, the update gate, takes the place of the reset gate r_t, as referred by the ordinary equation in Equation (7). Moreover, this study replaces the tanh with the ReLU in the candidate state$\hat{h}_t$, thereby altering Equation (9) into Equation (10). The specific contributions are emphasized in red."

$$\hat{h}_t = \text{ReLU}(W_{x\hat{h}}x_t) + U_{h\hat{h}}(z_t \cdot h_{t-1}) + b_{\hat{h}} \tag{10}$$

Final output

$$h_t = (1 - z_t) * h_{t-1} + z_t * \hat{h}_t \tag{11}$$

ReLU units have been shown to outperform sigmoid nonlinearities in deep learning algorithms. The final revised architecture of the GRU model is illustrated in Figure 7.

3.3 Two-state GRU strategy

A gated recurrent unit is an advanced type of conventional RNN specifically designed for consecutive modeling. A recurrent layer requires the input value $h_t \in R^n$ at each time step t, as well as the hidden state h_t, by following the recurrent method illustrated in equation (12):

$$h_t = f(W_{xt} + Uh_{t-1} + b) \tag{12}$$

Where $W \in R^{m\times n}$, $b \in R^{m\times m}$, $b \in R^m$, are the weights matrix and bias vector, respectively, and *f* represents the element-wise nonlinearity. Training RNNs to capture long-term dependencies is challenging due to issues like vanishing and exploding gradients [25]. However, by incorporating gating mechanisms, GRUs can retain memory significantly longer than conventional RNNs. Recent studies have revealed that GRUs analyze words employing only the forward language context, making it incredible for them to acquire backward contexts. Consequently, we explored that linguistic processing relies on both forward and backward contexts for accurate sentence interpretation. To address the aforementioned issue, we introduce the Two-State Feature Attention GRU (TS-FA-GRU). The proposed framework employs a two-stage attention strategy to enhance the extraction and utilization of textual features. This framework involves two distinct processes: the "forward pass" for a positive pass and the "backward pass" for a negative pass, as illustrated in Figure 10 . The TS-GRU effectively learns the context of words in both directions. Drawing inspiration from bidirectional recurrent neural networks (BRNNs) described in [42], TS-GRU employs two separate recurrent networks for the forward (left to right) and backward (right to left) passes during training, which are subsequently merged into the output layer. Equations (13 to 16) describe the forward direction of the TS-FA-GRU network, whereas equations (17 to 20) outline the backward direction. These all gates and states such as z_t, r_t, $\tilde{h}_t$, and h_t for both the forward and backward GRU are defined as follows:

Forward Pass:

$$\overrightarrow{z_t} = \sigma(\overrightarrow{W_{zx}}x_t) + \overrightarrow{U_{zh}}(\overrightarrow{h_{t-1}}) + \overrightarrow{b}_z \tag{13}$$

$$\overrightarrow{r_t} = \sigma(\overrightarrow{W_{rx}}x_t) + \overrightarrow{U_{rh}}(\overrightarrow{h_{t-1}}) + \overrightarrow{b_r} \tag{14}$$

$$\overrightarrow{\hat{h}_t} = \tanh(\overrightarrow{W_{\hat{h}}}x_t) + \overrightarrow{r_t} \cdot \overrightarrow{U_{\hat{h}}}(\overrightarrow{h_{t-1}}) + \overrightarrow{b_{\hat{h}}} \tag{15}$$

$$\overrightarrow{h_t} = (1 - \overrightarrow{z_t}) \cdot \overrightarrow{h_{t-1}} + \overrightarrow{z_t} \cdot \overrightarrow{\hat{h}_t} \tag{16}$$

Moreover, we incorporated a backward pass into the developed model to examine further valuable information.

Backward Pass:

$$\overleftarrow{z_t} = \sigma(\overleftarrow{W_{zx}}x_t) + \overleftarrow{U_{zh}}(\overleftarrow{h_{t-1}}) + \overleftarrow{b_z} \tag{17}$$

$$\overleftarrow{r_t} = \sigma(\overleftarrow{W_{rx}}x_t) + \overleftarrow{U_{rh}}(\overleftarrow{h_{t-1}}) + \overleftarrow{b_r} \tag{18}$$

$$\overleftarrow{\hat{h}}_t = \tanh(\overleftarrow{W}_{\hat{h}}x_t) + \overleftarrow{r}_t \cdot \overleftarrow{U_{\hat{h}}}(\overleftarrow{h_{t-1}}) + \overleftarrow{b_{\hat{h}}} \tag{19}$$

$$\overleftarrow{h_t} = (1 - \overleftarrow{z_t}) \cdot \overleftarrow{h_{t-1}} + \overleftarrow{z_t} \cdot \overleftarrow{\hat{h}}_t \tag{20}$$

The activation of a word at time t: donated as $h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}]$ = shows a random sequence (x_1,x_2,…,x_n) consisting n words, where each word at time t is depicted as a spatial vector.

The forward GRU executes $\overrightarrow{(}h_t)$, capturing the left-to-right contexts of the sentence, whereas the backward GRU captures the right-to-left contexts $\overleftarrow{(h_t)}$. These forward and

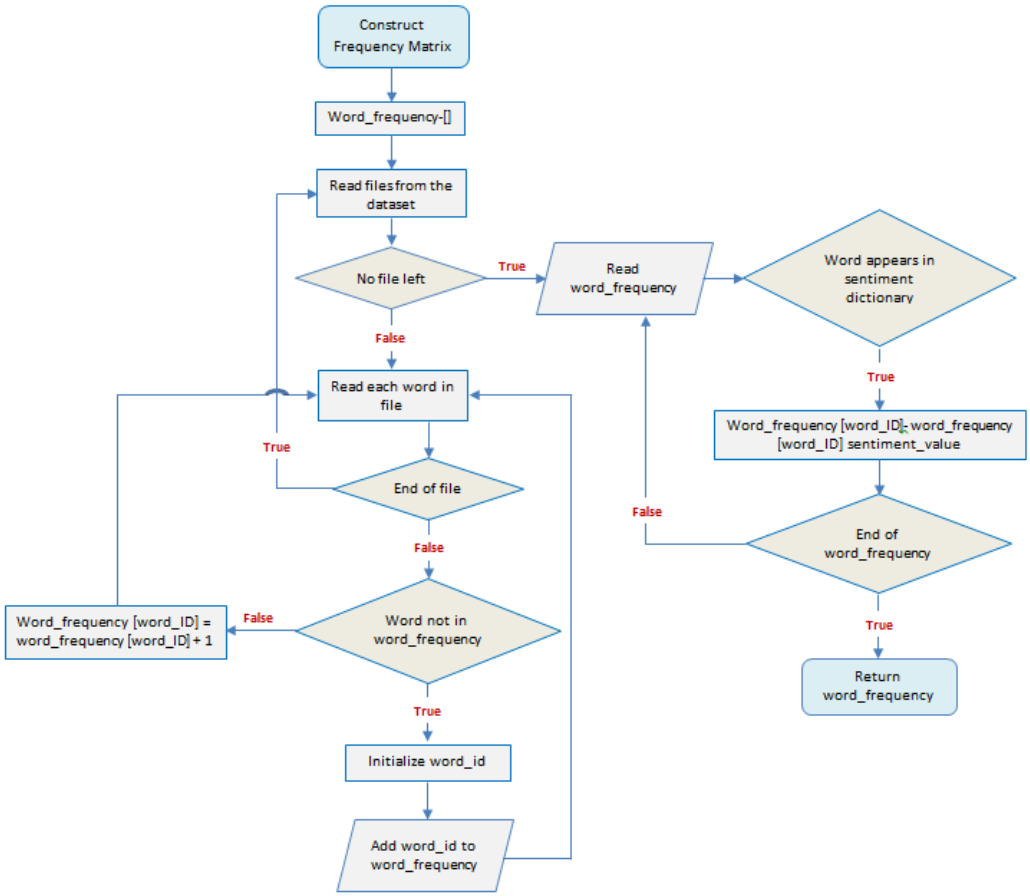


Figure 5: Flowchart illustration of build_vocab function

backward context representations are then joined into a single context. Our proposed mechanism effectively extracts valuable information, which expressively enhances the accuracy of text classification.

3.4 Pre-feature attention TS-GRU

The Pre-feature attention TS-GRU framework is designed to integrate both words and their context to form an initial understanding for sentiment recognition. GRU and LSTM models often struggle to extract essential information for effective text classification, particularly with longer input sequences [43]. However, specific words play a crucial role in enhancing classification accuracy. Within the two-state feature-attention GRU architecture, the attention mechanism is vital for extracting useful information from lengthy reviews [44], aiding in the classification of emotions at the word level. Furthermore, the GRU's gating mechanism regulates the flow of information, and the two-state GRU strategy effectively integrates data from both preceding and succeeding connections [45]. The pre-feature strategy involves both forward and backward sub-states. The forward sub-state processes sequential words from the embedding layer from start to finish, whereas the backward sub-state processes them in reverse order. At any given time step t, for an input word embedding x^k, the forward candidate states $\overrightarrow{h_{t-1}}$ and $\overrightarrow{h_t}$, along with the backward candidate states $\overleftarrow{h_t}$ and $\overleftarrow{h_{t-1}}$, are initialized in the TS-GRU as demonstrated in equations (21, 22, 23):

$$\tilde{h}_t = \tanh(\overrightarrow{W_x^{(\tilde{h})} x_t} + \overrightarrow{r_t} \cdot \overrightarrow{U^{(\tilde{h})} h_{t-1}} + \overrightarrow{b_{\tilde{h}}}) \tag{21}$$

$$\tilde{h}_t = \tanh(\overleftarrow{W_x^{(\tilde{h})} x_t} + \overleftarrow{r_t} \cdot \overleftarrow{U^{(\tilde{h})} h_{t-1}} + \overleftarrow{b_{\tilde{h}}}) \tag{22}$$

$$\bar{h} = \left(V \left[\overrightarrow{\tilde{h}_t} : \overleftarrow{\tilde{h}_t} \right] + k \right) \tag{23}$$

3.5 Attention strategy for word-feature seizing

In the feature-attention process, after obtaining the final output from the first layer's hidden state, we employed an attention strategy that help to identify word polarity by focusing on valuable information in the contextual sentence. The detailed design of the feature attention strategy exploited in our developed approach is shown in Figure 9. Furthermore, Figure 9 demonstrates the dispersal of o_t^k and

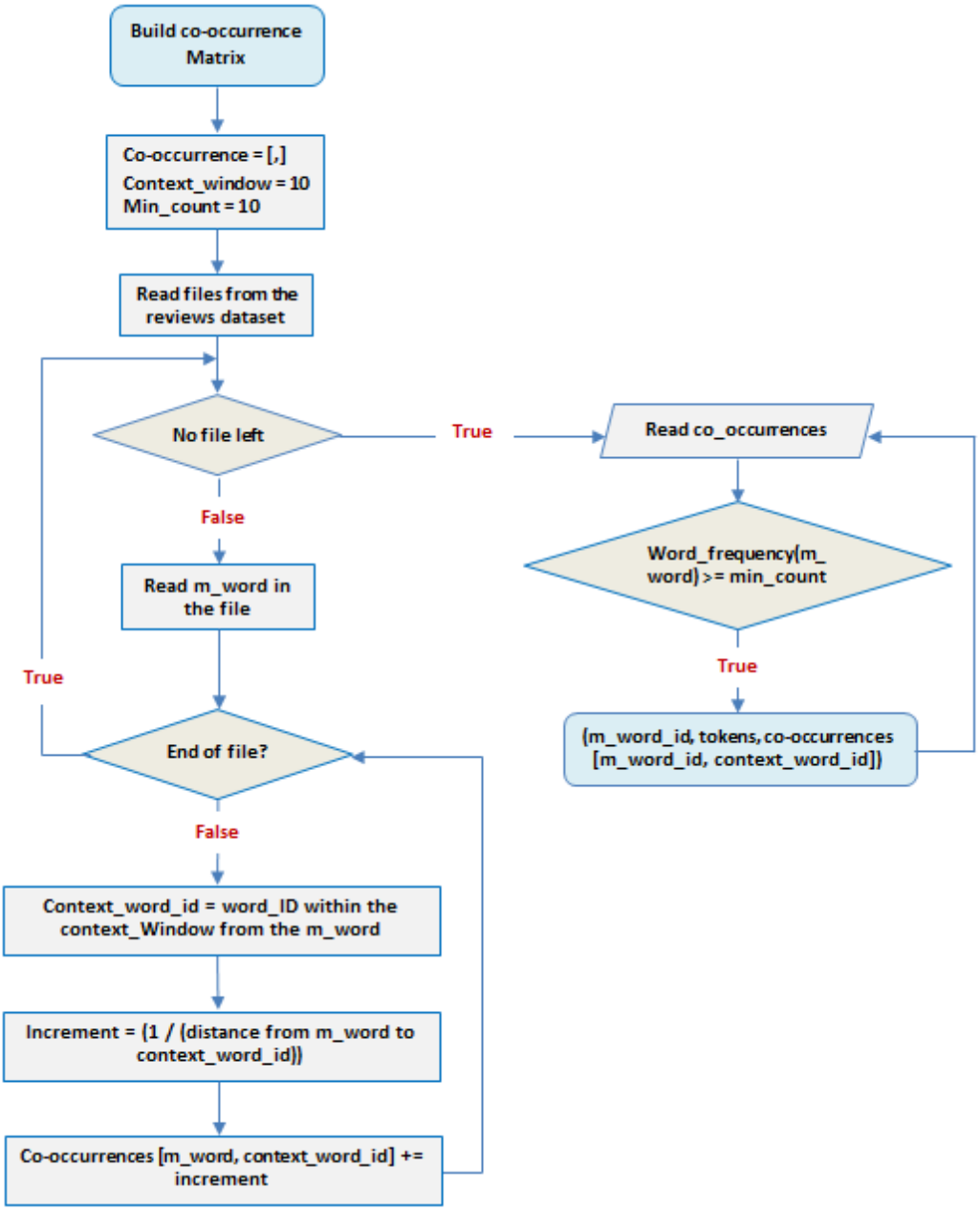


Figure 6: Flowchart illustration of the build cooccurrence function

k^{th} time step, generated by the attention strategy, as follows:

$$o_t^k = \frac{\exp(e_t^k)}{\sum_{i=1}^{m} \exp(e_t^i)} \tag{24}$$

The numerical notation for the memory cell at the e_t^k time step is denoted as k^{th}, and is illustrated in equation 25:

$$e_t^k = [c_{t-1}^T h_1, c_{t-1}^T h_2, \ldots, c_{t-1}^T h_m] \tag{25}$$

Where h_k represents the hidden state of the pre-feature attention TS-GRU, and the memory function at the c_{t-1} at k^{th} time step in the post-feature attention GRU is denoted as c_{t-1}. The target output is then achieved via equation (26) as follows:

$$o_t = \sum_{k=1}^{m} o_t^k h_k \tag{26}$$

3.6 Post-feature attention TS-GRU

Utilizing the feature attention strategy, the post-feature attention mechanism is applied, which further improves these features to gather comprehensive sentence-level information over iterative learning. This stage mimics the human decoding process, where context and relevance are continuously evaluated to improve understanding. The post-

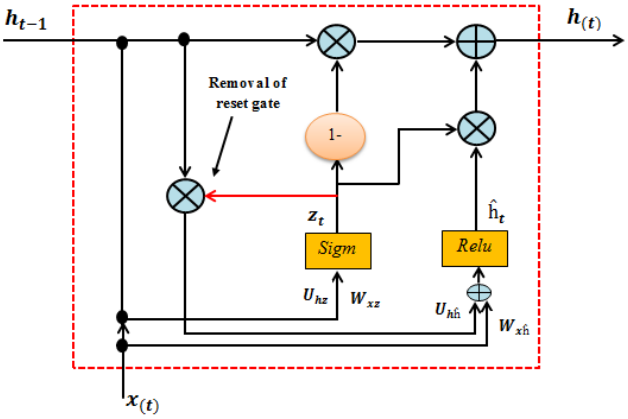


Figure 7: GRU structure excluding the reset gate

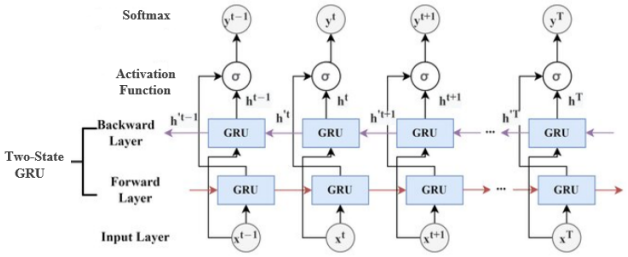


Figure 8: The developed "Two-State GRU strategy for text classification

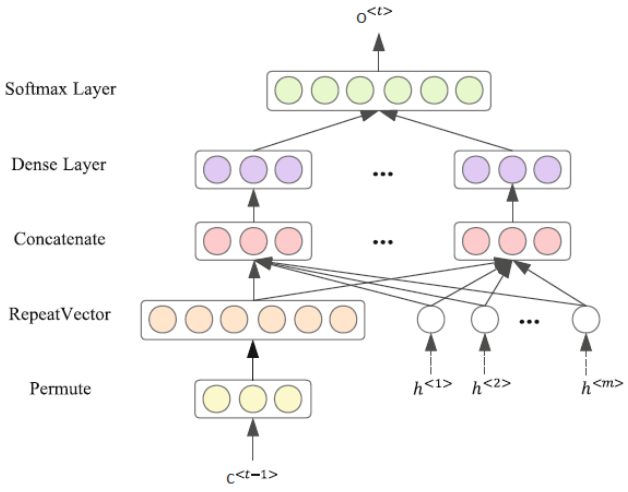


Figure 9: Brief design of feature attention strategy

feature attention TS-GRU integrates the outputs from the initial stage and the attention strategy, ensuring that the developed approach can emphasize vital predictive features. This dual attention strategy allows for Post-Feature Attention TS-GRU which efficiently accomplishes long-term dependencies and intricate patterns in the text, leading to enhanced accuracy in classification tasks. The main equation of the post-feature attention TS-GRU aligns with the typical Bi-GRU, except for the candidate cell, as shown in equation (27):

$$\tilde{h}_t = \tanh(W_x^{(\tilde{h})} x_t + r_t \cdot U^{(\tilde{h})} h_{t-1} + b_{(\tilde{h})}) \quad (27)$$

Thus, the output feature vector from the post-feature attention TS-GRU is passed through a dense layer to serve as the word representation. Finally, a softmax classifier is utilized to predict the class label ("positive" or "negative") for the text classification datasets. It has been noted that extracting and selecting features play a crucial role in enhancing the model's accuracy, as they directly influence its overall performance. Consequently, we introduced the Two-State Feature Attention Two-State GRU (TS-FA-GRU) mechanism specifically for text classification. The comprehensive architecture of the TS-FA-GRU model is demonstrated in Figure 10.

3.7 Developed flowchart

This study presents a systematic approach to text classification, illustrated in the flowchart depicted in Fig. 11. The four-stage process commences with data preprocessing, tailored to text classification objectives. The second stage involves initializing parameters for the developed TS-FA-GRU approach, where an embedding layer transforms words into real-valued vectors, capturing semantic, and syntactic details. Specifically, pre-trained GloVe embeddings are utilized to convert words into vectors, followed by the implementation of two-state GRU integrated with feature attention strategy for extracting more useful features. The third stage monitors training error comparative to a predetermined threshold. Finally, the fourth stage encompasses testing and verification. To assess performance, accuracy, execution time, and error rate are employed as evaluation metrics for text classification tasks. The findings underscore the importance of feature extraction and selection in enhancing model accuracy, as these processes directly impact the model's ultimate performance. To address this, the proposed Feature Attention Two-State GRU mechanism offers an effective solution for sentiment analysis. The findings indicate that effective feature extraction and selection are crucial for enhancing the model's accuracy, as they directly impact its overall performance. To address this, the developed TS-FA-GRU approach has been developed specifically for text classification.

4 Experimental setup

All simulations in this study were conducted on a system with an Intel Core i7-3770 CPU @ 3.40 GHz, equipped with 16 GB of RAM, and operating on Windows 10. Data pre processing and examination were performed using Python 3.9 within the Anaconda development environment, leveraging TensorFlow 1.14 and Keras 2.4 libraries. Moreover, we present a brief overview of our chosen datasets and the hyper parameter configurations used to optimize our proposed model in the following subsection

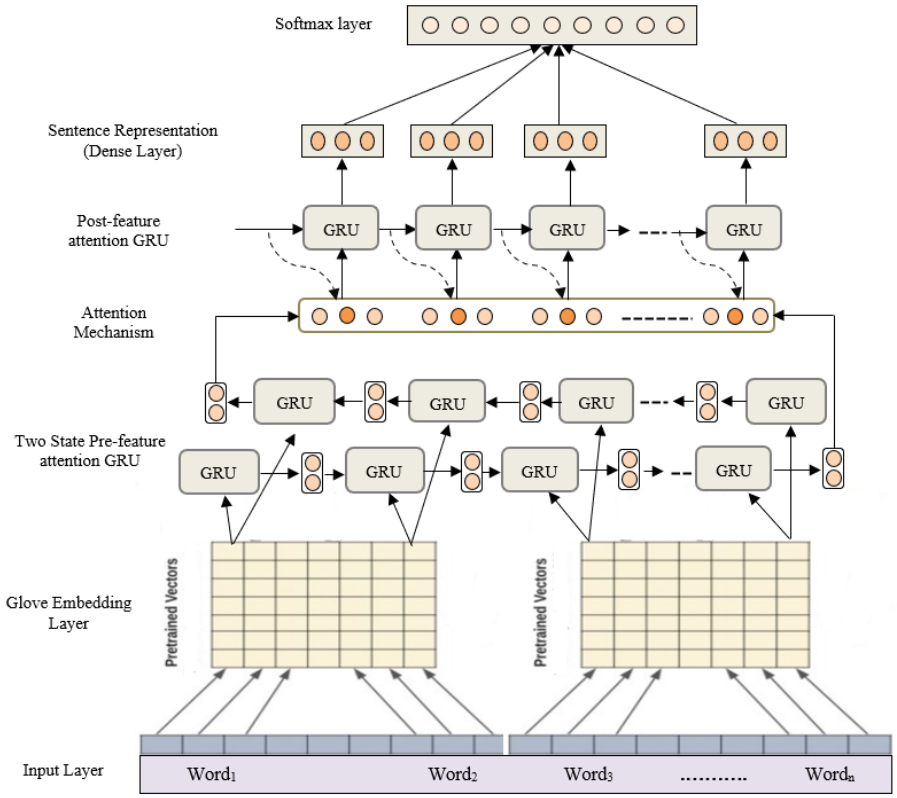


Figure 10: Complete framework of the developed two-state feature attention GRU (TS-FA-GRU)

4.1 Datasets description

In this study, we used five publicly available text classification datasets to evaluate the performance of our proposed model. These text classification datasets included: 20NG, R21578, AG's News, IMDB, and Amazon reviews, and publicly available on https://www.kaggle.com/. To maintain consistency, these datasets were employed for both training and testing in our experiments. This study provides a detailed description of each benchmark dataset used to assess the proposed and traditional approaches. Each dataset represents unique properties and challenges, contributing to a complete evaluation of the model's capabilities. Table 2 refers to a summary of the descriptive statistics for these datasets.

4.2 Data preprocessing steps

Text preprocessing is essential for preparing raw text data for analysis, and plays an important role in the model's performance. The first step in text mining and its applications involves converting unstructured text into a structured format to enhance the quality of the text dataset through preprocessing techniques. These steps are as follows:

Text Cleaning: In this step, we remove unwanted elements from raw text, such as numbers, extra space, and special characters, to make the data more structured. For instance, punctuation and emojis are often removed to emphasize the textual content.

Tokenization: Tokenization splits a text stream into smaller units, such as words, phrases, or other meaningful tokens for easier analysis. The primary goal of tokenization is to analyze and identify the individual words within a sentence.

Stop Word Removal: This stage involves eliminating frequently occurring words that carry little to no meaningful information, filtered out before or after processing natural language data. These common words such as "the," "an," "is," "and," "of," "but," and similar terms. Removing stop words helps emphasize the more meaningful words in the dataset.

Lemmatization: Lemmatization reduces words to their base or root form, considering their grammatical context. For example, "working", "worked", and "works" are converted to "work," preserving the original meaning. Handling Missing Data: Missing text entries are removed or replaced with placeholder values like "Unknown." This ensures the dataset is complete for modeling without introducing biases.

Dimension Reduction: In a text corpus comprising hundreds of thousands of words, it becomes impractical to classify them as features, as it may lead to computational challenges. Therefore, selecting the most representative features is vital to optimize the input for the classification process.

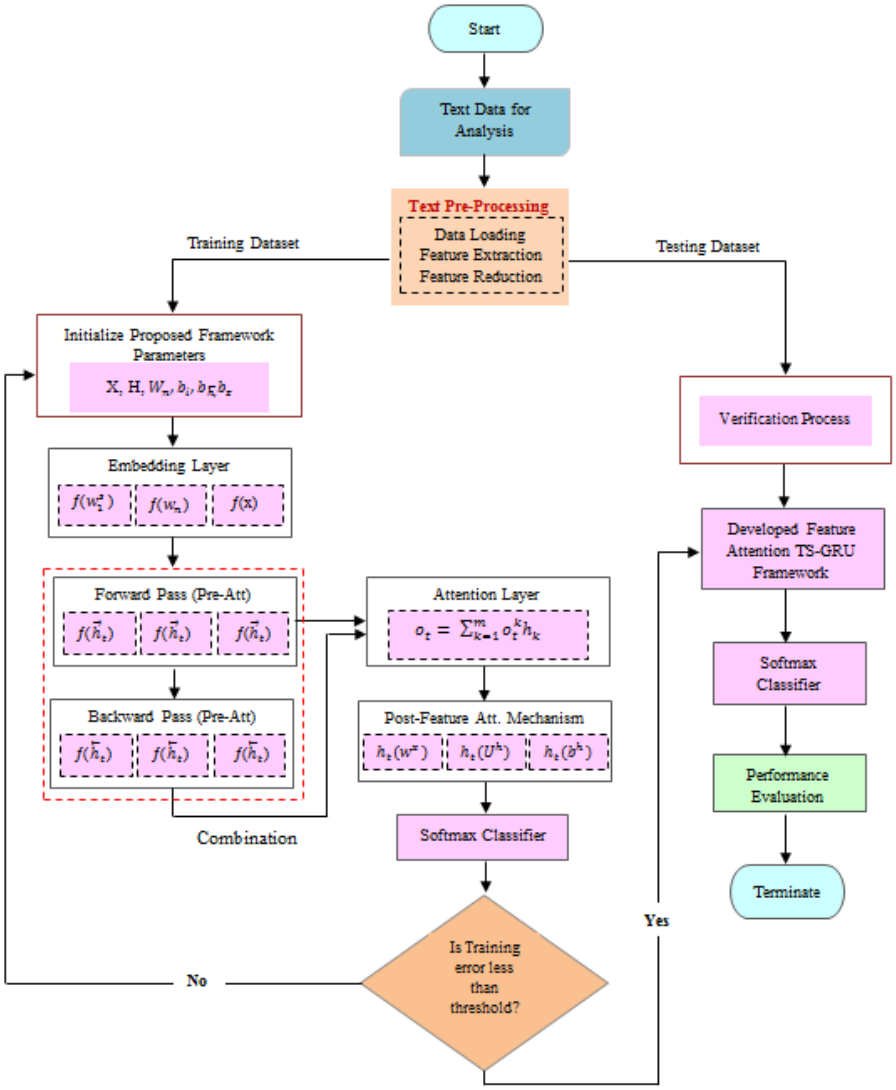


Figure 11: Developed flowchart

Table 2: Descriptive statistics of datasets

Datasets	Train Samples	Test Samples	Average lengths	Classes	Tasks
AG's News	150,000	80,000	42	4	News categorization
R21578	14,600	6400	74	12	Text classification
20NG	10,500	4500	86	15	News classification
IMDB	34,500	15,500	55	2	Sentiment analysis
Amazon Reviews	172,000	77,000	54	2	Sentence classification

4.3 Implementation detail

To optimize the effectiveness of the developed model, we start by improving the quality of the dataset. This study enhances the text dataset by applying pre processing methods, including the removal of stop words (e.g., ”and,” ”our,” ”of,” ”the,” ”to”) and punctuation. We refrain from using stemming during sentence embedding training to preserve all original information. The word embeddings are initialized using 300-dimensional pre-trained GloVe vectors by Pennington et al. [46]. To boost text classification effectiveness, well-ordered training policies for word vectors were employed, as discussed in previous research [47]. A consistent set of embeddings was used to achieve better generalization across datasets based on 30 iterations. During training, the Adam optimizer [48] was utilized with a learning rate of 0.001, and based on available memory we set a mini-batch size of 64. To combat over fitting, a dropout strategy [49] was implemented, including a

dropout rate of 0.5 applied to the output of the TS-GRU layers and a λr coefficient of 10-5 for L2 regularization. Figure 12 provides a configuration summary of each layer in the developed TS-FA-GRU model. The input layer is configured to handle sequences up to 300 words, with longer sentences truncated and shorter ones padded with zeros. The TS-FA-GRU layer comprises 128 memory nodes for both forward and backward passes. To mitigate over fitting, dropout is applied to the GRU layer with a 28% dropout rate for both the input (Dropout-W) and the hidden state (Dropout-U). An additional dropout layer is incorporated after merging the forward and backward GRU layers, with 46% of the input dropped to further reduce over fitting. Finally, a Dense layer was used for sentence illustration, outputting positive or negative predictions. A sigmoid activation function was employed to classify the sentences into two classes, resulting in either a 0 or 1.

4.4 Evaluation matrices

Various evaluation metrics have been used to assess the effectiveness of both the developed approach and conventional approaches in addressing text classification challenges. These metrics include accuracy, precision, recall, F-measure, and error rate/convergence. Precision and recall are among the most frequently utilized assessment metrics, alongside accuracy, for assessing the performance of an approach. Precision measures the accuracy by demonstrating the proportion of correctly classified positive instances among all instances predicted as positive. A higher precision value signifies that the network efficiently classifies true positive cases. Recall, also referred to as sensitivity, signifies the ratio of true positive instances (TP) to the total actual positive cases (TP + FN). The F1 score provides a weighted average of precision and recall, making it a widely used metric for balancing and optimizing a model's performance toward either precision or recall.

$$\text{Accuracy} = \frac{\text{TP}_{(n)}^{(m)} + \text{TN}_{(n)}^{(m)}}{\text{TP}_{(n)}^{(m)} + \text{FP}_{(n)}^{(m)} + \text{FN}_{(n)}^{(m)} + \text{TN}_{(n)}^{(m)}} \quad (28)$$

$$\text{Precision} = \frac{\text{TP}_{(n)}^{(m)}}{\text{TP}_{(n)}^{(m)} + \text{FP}_{(n)}^{(m)}} \quad (29)$$

$$\text{Recall} = \frac{\text{TP}_{(n)}^{(m)}}{\text{TP}_{(n)}^{(m)} + \text{FN}_{(n)}^{(m)}} \quad (30)$$

$$\text{F1 score} = \frac{2 \times \text{Precision}_{(n)}^{(m)} \times \text{Recall}_{(n)}^{(m)}}{\text{Precision}_{(n)}^{(m)} + \text{Recall}_{(n)}^{(m)}} \quad (31)$$

$$\text{Errorrate} = \frac{\text{FP}_{(n)}^{(m)} + \text{FN}_{(n)}^{(m)}}{\text{TP}_{(n)}^{(m)} + \text{TN}_{(n)}^{(m)} + \text{FP}_{(n)}^{(m)} + \text{FN}_{(n)}^{(m)}} \quad (32)$$

5 Results and discussion

In our experimental findings, we present a brief overview of the simulation results for the proposed TS-FA-GRU model, comparing its performance with traditional deep learning models across five different text classification datasets. The evaluation, based on several performance metrics, highlights the significant accuracy achieved by our model for each benchmark dataset.

5.1 Convergence rate

This section describes an experimental evaluation of the developed model with the selected datasets. Figure 17 , 13, 14, 15 and 16 illustrate the learning convergence of the developed and the traditional approaches in text classification tasks. The convergence rate of the proposed TS-FA-GRU model was employed using five benchmark text categorization datasets. We evaluated the convergence rates throughout 30 epochs. It was observed that the error rates for the proposed and comparative algorithms stabilized after 28 epochs. Experimentally, the proposed and comparative approaches demonstrated relatively better convergence on the 20NG, R21578, and IMDB datasets. The AG News and Amazon review datasets are more complex than the 20NG, R21578, and IMDB datasets, causing some interruptions in the convergence rate for all approaches. However, the proposed TS-FA-GRU approach maintained its convergence throughout the 30 epochs, AG News, and Amazon review. It showed slow convergence for all comparative approaches except for the TS-FA-GRU. Moreover, the recurrent approaches, like TS-FA-GRU, Bi-GRU, and Bi-LSTM, performed better on all text classification dataset compared to other traditional approaches including LSTM, GRU, and CNN. The convergence results indicate that the proposed model, incorporating two-state and feature attention mechanism, exhibits excellent performance with faster convergence than the other comparative approaches.

5.2 Accuracy-based analysis

The accuracy-based analysis of the proposed TS-FA-GRU model was also carried out using five benchmark text datasets such as 20NG, R21578, AG News, IMDB, and Amazon review. The evaluation highlighted the model's superior performance, illustrating consistently better accuracy rates across all datasets when compared to traditional deep learning approaches. We evaluated the performance of the developed approach against other methods, including LSTM, GRU, CNN, Bi-LSTM, and Bi-GRU models. Our empirical outcomes showed that the developed approach achieved excellent accuracy across all five datasets compared to these alternative models. These results underscore the effectiveness of the TS-FA-GRU approach in accurately classifying text, indicating its robustness and reliability in various NLP tasks. Table 3 demonstrates the performance

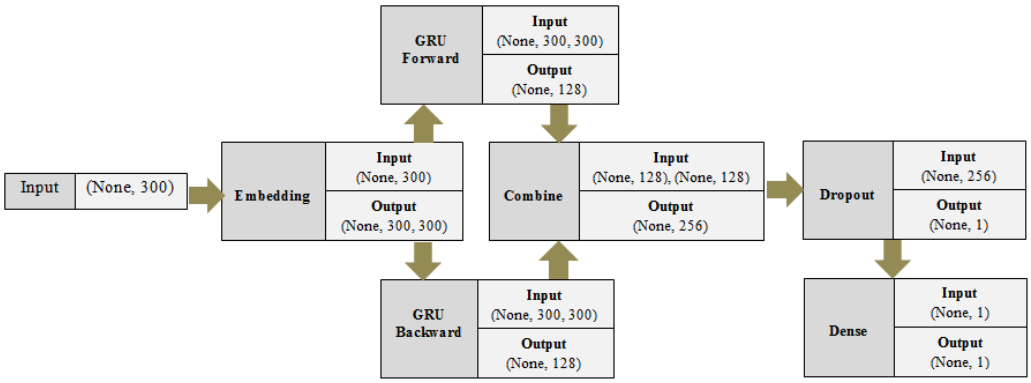


Figure 12: Proposed TS-GRU model configuration

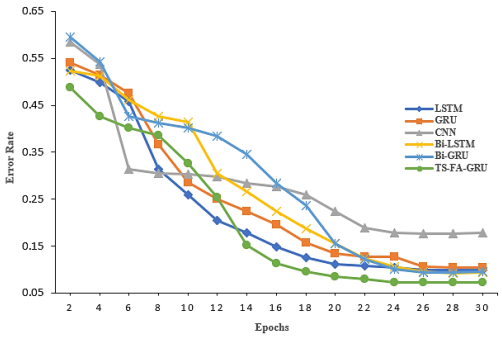


Figure 13: 20NG dataset

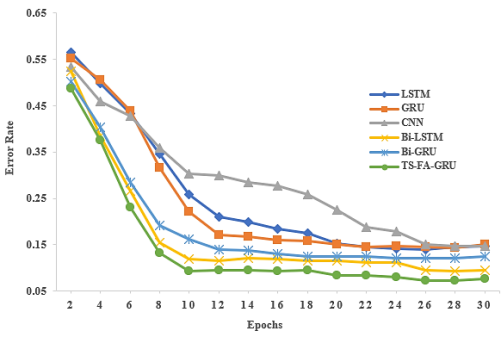


Figure 15: IMDB dataset

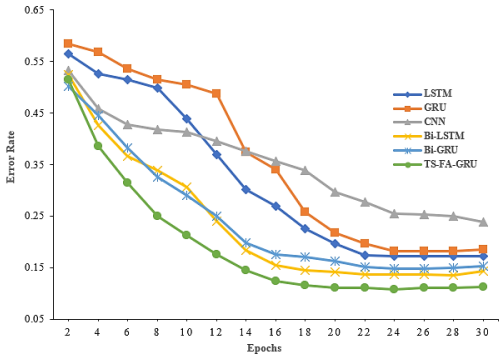


Figure 14: R21578 dataset

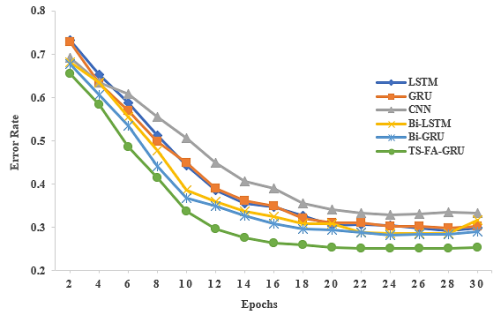


Figure 16: Amazon review dataset

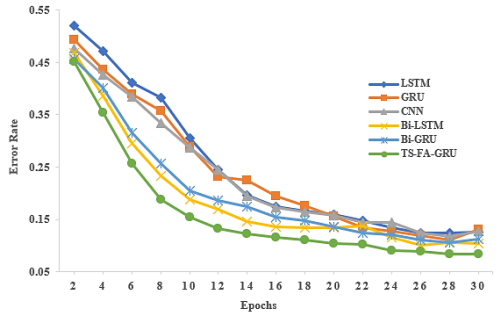


Figure 17: Convergence rate of proposed and comparative models on all respective Fig. 13, 14, 15, 16 datasets

comparison between our developed approaches and traditional approaches across diverse datasets.

5.3 Precision, recall, and F1-score evaluation

The proposed TS-FA-GRU approach was rigorously assessed employing precision, recall, and F1-score metrics across five benchmark text datasets. Precision, which measures the accuracy of positive predictions, showed notable developments with the TS-FA-GRU model compared to conventional approaches. The recall, which evaluates the model's capability to accurately identify all relevant oc-

Table 3: Classification accuracy of proposed and comparative approaches across all distinct datasets

Models	**20NG**	**R21578**	**AG's news**	**IMDB**	**Amazon**
LSTM	89.49	88.41	89.75	86.81	84.27
GRU	90.18	89.01	88.42	86.28	84.92
CNN	88.13	86.36	89.52	85.42	83.97
Bi-LSTM	91.29	90.52	91.45	89.98	85.14
Bi-GRU	90.83	90.18	90.71	89.59	85.79
TS-FA-GRU	93.86	92.69	94.73	92.46	88.23

currences, was also significantly higher in the developed model. This demonstrates its strong capability in capturing the true positives, ensuring that relevant data is not overlooked. Subsequently, the F1-score, which delivers a harmonic mean of precision and recall, further emphasizes the superiority of the TS-FA-GRU model. The higher F1-scores across all datasets highlight the balanced performance of the model. These metrics jointly determine that the proposed approach not only excels in making accurate predictions but also in identifying all relevant instances, offering a comprehensive improvement over conventional deep learning models in text classification tasks. Tables 4,5,6, 7, and 8 display the comparison performance of the developed approach and conventional models. Moreover, as the complexity of the datasets increases, the TS-FA-GRU model demonstrates superior performance than the LSTM, GRU, CNN, Bi-LSTM, and Bi-GRU approaches. In concluded, the proposed model delivered outstanding results, outperforming several conventional approaches in terms of accuracy, particularly on all benchmark datasets.

Table 4: Performance analysis of developed and standard approaches using 20NG dataset

Models	Precision	Recall	F1-score
LSTM	88.92	86.12	87.49
GRU	87.42	88.22	87.94
CNN	85.41	83.65	84.53
Bi-LSTM	91.04	90.16	90.60
Bi-GRU	88.48	90.92	89.64
TS-FA-GRU	92.02	93.18	92.60

Table 5: Performance analysis of developed and traditional models using the R21578 dataset

Models	Precision	Recall	F1-score
LSTM	87.08	88.45	87.74
GRU	86.65	87.68	86.98
CNN	84.60	85.58	84.96
Bi-LSTM	86.54	87.24	86.88
Bi-GRU	88.32	86.56	87.42
TS-FA-GRU	91.72	90.17	90.93

Table 6: Performance analysis of developed and traditional models using AG New's dataset

Models	Precision	Recall	F1-score
LSTM	87.68	85.92	86.56
GRU	89.62	85.84	87.32
CNN	86.31	89.16	87.72
Bi-LSTM	91.35	89.29	90.28
Bi-GRU	90.76	87.82	89.27
TS-FA-GRU	94.04	92.28	93.16

Table 7: Performance analysis of developed and traditional models using IMDB dataset

Models	Precision	Recall	F1-score
LSTM	87.22	86.65	86.93
GRU	88.16	86.42	87.15
CNN	87.74	85.24	86.58
Bi-LSTM	89.52	87.66	88.48
Bi-GRU	90.89	90.42	90.65
TS-FA-GRU	93.24	91.16	92.19

Table 8: Performance analysis of developed and traditional models using Amazon review dataset

Models	Precision	Recall	F1-score
LSTM	79.52	77.28	78.12
GRU	80.77	79.45	79.86
CNN	82.93	81.63	82.27
Bi-LSTM	81.86	84.29	83.05
Bi-GRU	83.19	82.38	82.79
TS-FA-GRU	86.32	84.48	85.40

5.4 Execution time comparison

This study evaluated the execution time performance of the developed model and compared it with standard approaches utilized in all datasets. The computational efficiency of all models depends on the hardware, software, and compiler configurations. To ensure a fair comparison, this research employed the same software setup and hardware combi-

nation for the developed and comparative models. Table 9 illustrates a comparative analysis of the execution times for the developed TS-FA-GRU approach and other traditional approaches, including standard LSTM, GRU, CNN, Bi-LSTM, and Bi-GRU. On the first two datasets, 20NG and R21578, the traditional GRU approach exhibited comparatively better execution times than the developed TS-FA-GRU model due to the simplicity of the data. However, as the complexity and noise levels increase in datasets such as IMDB, AG news, and Amazon review, the developed approach demonstrates superior execution time performance compared to standard LSTM, GRU, CNN, B-LSTM, and Bi-GRU. The best results from the experiments are highlighted in bold.

5.5 Comparison analysis with traditional studies

This study assesses the efficacy of the developed approach by contrasting it with traditional studies, such as cited studies in [50], [51]. The comparison emphasizes on performance in terms of accuracy of the proposed approach using four different datasets: 20NG, AG News, Amazon review, and IMDB. Table 10 shown that our proposed approach consistently outperformed than traditional approaches in terms of accuracy, particularly as the dataset size increases. This enhancement is due to the better generation of textual features, which effectively expands the dataset and diminishes the significance of the initial dataset size. Moreover, our develop approach builds upon the strengths of earlier character-level methods, simplifying the implementation of various languages by openly updating the alphabet. All the experimental evaluations demonstrated that the TS-FA-GRU model consistently converged faster than existing deep learning models, showcasing its competence and effectiveness in attaining optimal performance across diverse datasets.

6 Conclusion and future direction

Text classification is a significant and broadly studied area in NLP. Among the different deep learning models used in NLP, the GRU is notably effective for sequential learning tasks. In this research, we proposed the Two-State Feature Attention GRU (TS-FA-GRU) model to demonstrate a significant improvement in text classification tasks. Our proposed approach leverages the word embedding layer's abilities to examine word polarity through sentential patterns and predict the sentiment in reviews. This research makes three key contributions: Firstly, we introduce the Two-State GRU (TS-GRU) structure to tackle text classification challenges. Secondly, we develop a novel sophisticated feature-attention mechanism that allows the model to dynamically focus on essential features, enhancing its ability to capture intricate dependencies and contextual information within the text through pre- and post-feature attention layers. Moreover, a post-feature attention GRU is employed to mimic the decoder's function, extracting targeted features acquired from the pre-feature attention TS-GRU and the attention layer. Thirdly, this research modifies the standard GRU by removing the reset gate and replacing it with an update gate in the candidate state. Furthermore, we utilized the ReLU activation function in the candidate state of the GRU network instead of the tanh activation function, while softmax is employed as the final output layer for text classification. Through comprehensive evaluations, we conducted experiments using five benchmark datasets such as 20NG, R21578, IMDB, AG News, and Amazon review, the proposed TS-FA-GRU model consistently demonstrated superior accuracy, precision, recall, and F1-score compared to traditional models such as LSTM, GRU, CNN, Bi-LSTM, and Bi-GRU. For future direction, we identified the computational complexity of the proposed model, and attributed the two-state strategy, as an area for improvement. Reducing this complexity throughout the model's processes is a key direction for future research to enhance the model's efficiency. Additionally, we aim to design a more efficient and versatile attention architecture at the word-feature level while also minimizing the overall execution time and computational cost of the developed framework. Additionally, our goal is to create a more efficient and flexible attention structure at the word-feature level, while also minimizing the overall computational cost of the framework we've developed.

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Table 9: Training times for different models on various datasets

Models	20NG	R21578	AG news	IMDB	Amazon
LSTM	12m 03s	13m 21s	39m 45s	27m 50s	50m 28s
GRU	11m 43s	10m 32s	34m 16s	22m 43s	45m 30s
CNN	19m 22s	17m 52s	49m 37s	39m 08s	57m 22s
Bi-LSTM	17m 24s	19m 48s	55m 16s	40m 19s	1 h 14m 24s
Bi-GRU	16m 55s	17m 28s	48m 24s	34m 13s	1 h 02m 21s
TS-FA-GRU	14m 40s	15m 26s	40m 36s	31m 51s	55m 04s

Table 10: Comparison analysis with traditional studies in terms of accuracy

Methods	20NG	AG's news	Amazon	IMDB
ROBERTA+ULR [50]	58.19	85.19	—	—
SWEM-max [52]	—	91.80	—	—
SWEM-hier [52]	—	92.48	—	—
Generative LSTM[53]	—	90.70	—	—
Generative LSTM-Shard comp.[53]	—	90.60	—	—
OOD Methods [54]	87.44	—-	—	—
FastText (Word Matrix) [55]	82.04	90.18	—	—
FastText (Document Matrix) [55]	82.28	90.05	—	—
CCNN-GAN [56]	88.14	91.94	—	—
PV+GRU [55]	—	—	81.82	—
NAE-GRU [56]	—	—	87.43	—
CNN+LSTM [57]	—	—	88.20	—
XLNet-Large (ensemble) [58]	—	—	67.64	—
CNN+GRU [59]	—	—	87.50	—
FARNN-Att [57]	—	—	—	89.22
WALE-LSTM [58]	—	—	—	89.50
CNN-LSTM [59]	—	—	—	88.90
CBOW-D+CNN [60]	—	—	—	87.20
TS-FA-GRU (Proposed)	93.86	94.73	88.23	92.46

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Application of CNN-BiGRU-MHSA: A Self-Attention Mechanism Based Detection Method in Electronic Data Forensics

Yang Lei
Department of Investigation, Fujian Police College, Fuzhou 350007, China
E-mail: fzleyan@163.com

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In response to the shortcomings of the current file fragmentation detection technology in terms of accuracy and efficiency, this study proposes a file fragmentation detection method based on the multi-head self-attention mechanism. First, the traditional self-attention mechanism is optimized by introducing the concept of multi-dimensional features and multi-head feature detection. Second, a file fragmentation detection model is constructed by combining the optimized feature extraction method, bidirectional gated recurrent units, and convolutional neural networks. This model achieved classification accuracy as high as 99% and 98.9% on the GovDocs1 dataset and the Enron email dataset, respectively, with a mean square error as low as 0.08. In practical applications, the model achieved a high classification accuracy of 99.2%, a low classification time of 0.09 seconds, and a low false detection rate of 0.02%, demonstrating excellent detection performance. The detection algorithms and models designed in this study outperformed existing methods in both performance and practical application effectiveness. This integrated approach not only circumvents the constraints of conventional self-attention mechanisms in one-dimensional feature extraction but also augments the model's capacity to discern and extract multi-dimensional features in an efficacious manner. The results indicate that the model effectively improves the work efficiency in actual electronic data forensics, providing a new reference method for the field.

Povzetek: Predlagana je metoda za zaznavanje fragmentacije datotek, ki temelji na mehanizmu večglave samo-pozornosti (MHSA) za izboljšanje elektronske forenzike. Model združuje konvolucijske nevronske mreže (CNN), dvosmerne enote z zaprtimi ponavljajočimi se vrati (BiGRU) in optimiziran mehanizem samo-pozornosti.

1 Introduction

In today's rapid development of information technology, electronic data forensics has become an important means to combat cybercrime and maintain network security. As a fundamental element of electronic data forensics, the accuracy and efficiency of file fragmentation detection directly influence the efficacy of the resulting forensic analysis [1]. As data storage and transmission technologies have advanced, the phenomenon of file fragmentation has become more prevalent, increasing the difficulty of data reorganization and compromising the accuracy and integrity of forensic results [2-3]. Therefore, finding an accurate and fast method for identifying and reorganizing file fragments has become a pressing issue in the field of electronic data forensics. Traditional file fragmentation detection methods mainly rely on matching features at the head and tail of files, but it is often difficult to achieve the best results when dealing with highly random and complex file fragments [4]. In recent years, with the rapid development of artificial intelligence and deep learning (DL) technology, file fragment detection techniques based on machine learning and DL have gradually emerged. Among them, self-attention mechanism (SAM) is widely used due to its advantages in capturing long-range dependencies and global features [5]. However, most of the existing SAMs focus on unidimensional feature extraction, which limits the full utilization of multi-dimensional information. To overcome this limitation, this study proposes a file fragmentation detection method based on the multi-head self-attention (MHSA) mechanism, which significantly improves the accuracy and efficiency of file fragmentation detection by integrating multi-dimensional features and multi-head feature detection techniques.

The novelty of the research lies in the integration of convolutional neural network (CNN), bidirectional gated recurrent unit (BiGRU) and MHSA, which enables multi-dimensional feature extraction from file fragments. This integrated approach not only overcomes the limitations of traditional SAM in one-dimensional feature extraction, but also improves the recognition and extraction efficiency of the model for multi-dimensional features. This multi-modal feature extraction capability allows the model to more accurately identify and reorganize file fragments, improving the accuracy and integrity of electronic data forensics. The high classification accuracy and low false detection rate (FDR) of the model demonstrate that it can effectively improve the work efficiency in practical electronic data

forensics, especially when dealing with large amounts of data.

2 Related works

SAM, as a DL technique, better captures the relationships and dependencies between features by dynamically assigning attention weights to different parts when processing large amounts of data. To forecast drug-target interactions, Cheng et al. developed a DL model based on graph attention networks and the MHSA mechanism. The model was able to extract drug and protein features and evaluate important amino acid sequences in proteins through the attention mechanism. Ultimately, the drug-target interactions were predicted through the full connectivity layer. The outcomes indicated that the precision, recall, and F1 value of the model outperformed the existing methods on multiple datasets [6]. Shen et al. proposed a new SAM-based long short-term convolutional neural network (LS-CNN) model, which was designed to be utilized for network traffic (NT) grayscale image detection and Android malware classification tasks. The self-attentive LS-CNN model was created to take into account both the spatial and temporal aspects of NT after all of the NT had been transformed into grayscale images in chronological sequence. Self-attention weights were also introduced to concentrate on various input aspects. The outcomes indicated that this approach was able to reliably and thoroughly classify malware by category in addition to successfully detecting malware [7]. Tao et al. suggested an SAM-based code recommendation method for automatically finding useful code snippets in a programming context thus assisting the program in its programming task. The method first built a small candidate set from the codebase, and then utilized self-attention networks to capture the deep semantics of the code in an abstract syntax tree, and finally recommended the relevant code to the developer. Experimental results indicated that the model outperformed existing methods in terms of recall, accuracy, and cumulative gain of normalized discounting [8].

File fragmentation detection is an important part of data recovery and digital forensics. Its goal is to identify and reorganize the scattered file fragments on the storage media. File fragmentation detection in essence belongs to the research content in the field of feature recognition, and a number of scholars have studied this field. Coquenet et al. proposed a new end-to-end segmentation free architecture known as Document Attention Network and used this network for handwritten document recognition. The outcomes indicated that the model achieved a character error rate of 3.43% and 3.70% on the page level and double page level of the Document Image Evaluation Database 2016 version dataset, respectively, with a low overall error rate [9]. Li et al. proposed an effective multi-hot coding and classification module for text recognition tasks in multilingual or large character set scenarios. In addition, the study also designed a lightweight converter to combine with this classification module. Finally, it developed a lightweight scene text recognition framework. Experimental results indicated that the built lightweight scene text recognition framework performed well in multiple environments [10]. A multi-domain character distance perception module was proposed by Zheng et al. with the goal of recognizing visual and semantic features in fused scene text recognition. The module combined character spacing, orientation change and semantic affinity through positional embedding and cross-attention mechanisms. Experimental results demonstrated that the module performed well on several publicly available datasets, especially in dealing with problems such as text distortion and chaotic layout of characters [11]. A forensic intelligence system based on signed documents was developed by Widiyasono et al. The system was used to automatically match file extensions and signatures, to recognize file types, and to address the problem of document authenticity maintenance in information technology. The outcomes indicated that the system could detect and recover files with modified extensions while improving the efficiency of forensic investigations [12].

In summary, a number of experts have built file fragmentation detection models using various DL techniques and achieved certain research results. In addition, a number of experts have also proposed various mechanisms to optimize file fragmentation detection techniques. Although existing research has provided a variety of effective file fragmentation detection techniques, further research and optimization are still needed in practical applications, especially when dealing with highly randomized and complex file fragments. This research aims to optimize SAM and combine it with neural networks to improve this shortcoming so as to meet the special detection needs in the field of electronic data forensics. A comparison of existing methods is shown in Table 1.

Table 1: Comparison of different methods

Research	Key methods	Data sets	Limitations
Cheng et al. [6]	Graph attention networks and MHSA	Drug-target interaction data	Lack of specific applications for file fragmentation detection
Shen et al. [7]	SAM-based LS-CNN	Network traffic data	Inability to fully utilise multi-dimensional information
Tao et al. [8]	SAM-based code recommendation	Programming context data	Limited ability to recognise complex file fragments
Coquenet et al. [9]	Document attention networks	Handwritten document data	Not applicable to file fragmentation detection in electronic data forensics
Li et al. [10]	Multi-hot encoding and classification module	Multilingual text data	Limited ability to reconstruct file fragments

Zheng et al. [11]	Multi-domain character distance awareness module	Scenario text data	Insufficiently comprehensive extraction of file fragmentation features
Widiyasono et al. [12]	Signature document-based forensic intelligence system	Signed document data	Limited ability to detect and recover file fragments
This study	CNN-BiGRU-MHSA	GovDocs1, Enron mail dataset	-

3 Methods and materials

For fully extracting the file fragmentation information in electronic data, the study firstly features the file fragments in electronic data forensics. Secondly, a new fragmentation detection model is built by combining MHSA mechanism with two neural network structures.

3.1 Approaches to document fragmentation in electronic data forensics

3.1.1 Conventional methods of file fragmentation processing and detection

A subset of technology known as "electronic data forensics" makes use of laws, regulations, and computer information technology to gather, examine, and preserve electronic data that may be used as proof in court. This technology is now widely used in cybercrime investigations, corporate data leakage incidents, intellectual property protection and other fields. In the process of electronic data forensics. It involves a variety of technical means, including data recovery, file analysis, NT monitoring, and log auditing and so on. Among them, file fragmentation detection used in the file analysis process has a key role [13-14]. During the process of data storage and transmission, files may be split into multiple discrete fragments and stored in different locations due to various reasons, such as system crashes, disk damage, file deletion, lack of storage space and network transmission interruptions. These fragmented files pose a great challenge to forensic work. Therefore, these scattered fragments must be reassembled to recover the content of the original file. The file fragmentation detection process in electronic data forensics is shown in Figure 1.

In Figure 1, firstly, the file data needs to be read. Secondly, determine whether the file data is complete or not. If the file data is not complete, further check whether it can be optimized for processing. If it cannot be optimized, the file recovery operation is carried out directly. If it can be optimized, then enter the file fragmentation type detection step to identify and classify file fragments. After the detection is complete, return to the process and continue with the file recovery step. During the file recovery process, attempts are made to rejoin the detected file fragments and recover them as complete file data. Finally, the recovered complete file data is input into other processes of digital forensics for further analysis and processing, thereby completing the entire forensic process. In the file fragmentation type detection task, the file header is a distinguishing mark used to identify different file types. Currently there are three common ways to view file types in computers, which are the viewing of the file's attributes, displaying the file format's suffix, and displaying the file's details. However, these viewing methods fail when the file type is tampered with, resulting in the loss of information such as file signatures or file headers. Therefore, understanding the format and storage structure of file types enables better identification of different types of files. Common file types and extensions in electronic data forensics are shown in Figure 2.

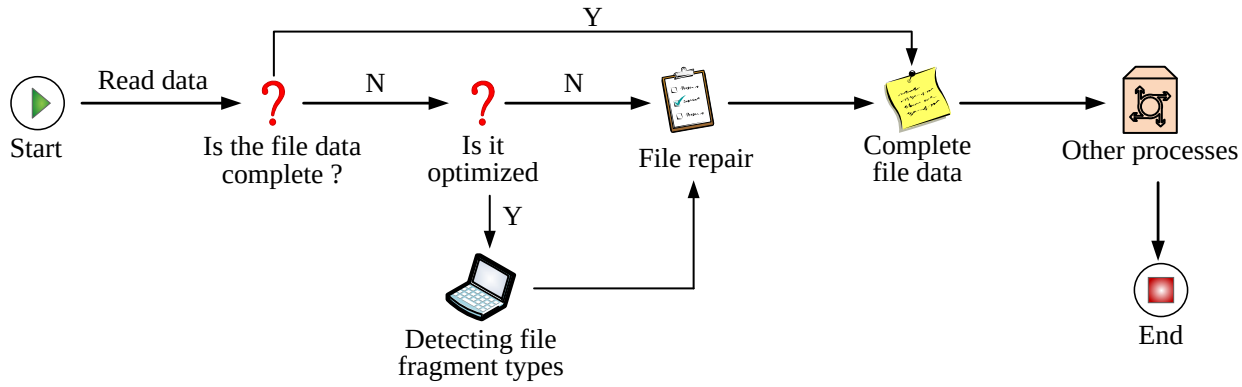


Figure 1: Flowchart of file fragmentation detection in electronic data forensics

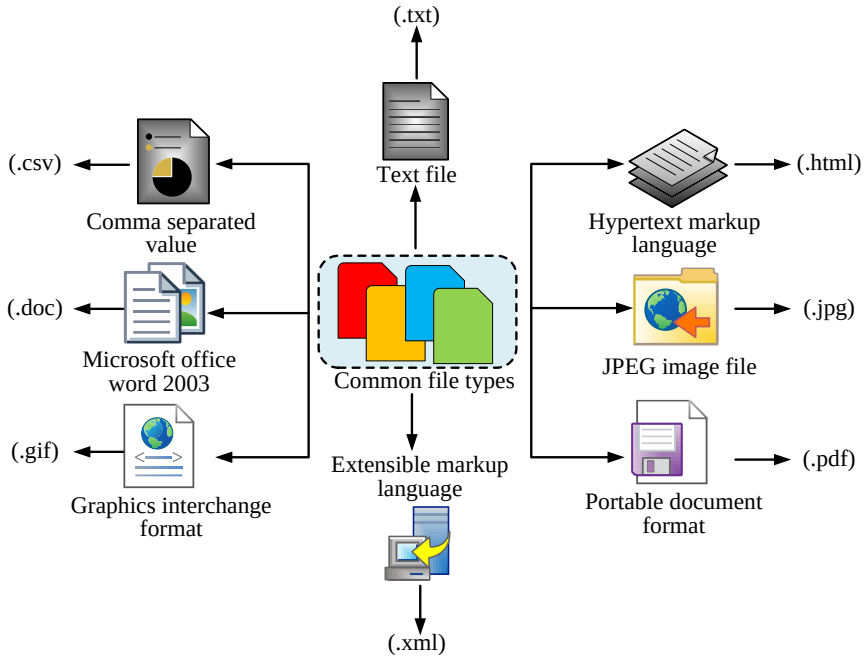


Figure 2: Common file types and extensions in electronic data forensics

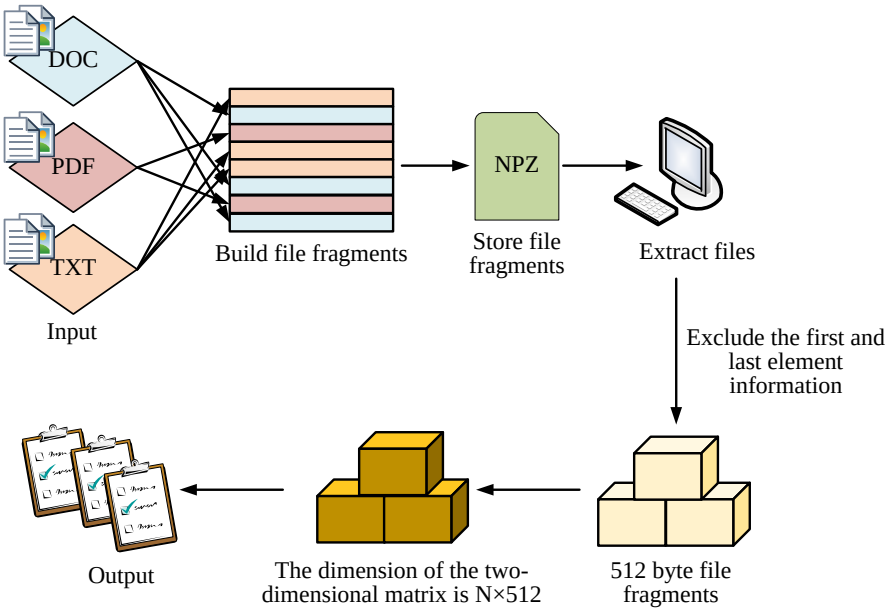


Figure 3: Construction and conversion process of file fragmentation

In Figure 2, a common file type in electronic data forensics is often exemplified by the comma-separated value file type, which can be notated with the .csv extension. Therefore, when performing file fragmentation detection, accurate fragmentation classification can be performed by recognizing these file types and file extensions. The similar files after classification are pieced together to ensure that the files can be recovered accurately [15-16]. In addition to recognizing file extensions to accomplish the fragmentation detection task, it is also possible to improve the detection accuracy by transforming the manifestation of fragmentation features. Currently, traditional fragmentation feature extraction methods rely on manual extraction, which is limited and inefficient. Considering that neural networks are excellent in automatically learning complex features, the study will use neural networks for fragmentation detection.

3.1.2 Document fragmentation data preprocessing

According to the file fragment detection method analysed in the previous section, the study first preprocessed the data. To fully extract the information of file fragments in electronic data, the file fragments are first characterized in electronic data forensics. In the data preprocessing

stage, the steps shown in Figure 3 are taken to ensure the diversity and representativeness of the data, as well as the effectiveness of model training prior to detection.

In Figure 3, firstly, it is necessary to split multiple types of files into multiple small fragments to construct the experimental dataset to ensure the diversity and representativeness of the data. Second, these file fragments are preprocessed. The first and last meta-information of the files are removed, the core content is retained, and the consistency and purity of the data are ensured. The first and last meta-information typically contain non-content information such as the file's path and size, which are not important for identifying and restructuring the file's content and can introduce noise that degrades the model's performance. Instead, the core content of the file fragment is retained, allowing the model to focus on the actual content of the file for feature extraction and learning. Then, the preprocessed file fragments are fixedly partitioned according to 512-byte size to form small units suitable for neural network processing. Finally, these fixed-size file fragments are converted into a two-dimensional matrix. The dimension of the matrix is the number of fragments N×512 to facilitate subsequent feature extraction and model training. Through the above steps, the file fragments can be efficiently converted into a data format suitable for neural network processing, thereby facilitating feature extraction. The Z-score standardization method was also used to standardize the data. This method transforms the data by subtracting the mean and dividing by the standard deviation so that the data set has a mean of 0 and a standard deviation of 1. The specific standardization formula is shown in Equation (1).

$$\kappa = \frac{(x-\mu)}{\vartheta} \tag{1}$$

In Equation (1), x denotes raw data. μ denotes mean. ϑ denotes standard deviation. κ denotes standardised data. The dataset is divided into training and test sets in 8:2 ratio, where the training set mean attribute is $\mu_{train}=0.0$ and variance is $\vartheta^2_{train}=1.0$. The test set mean attribute is $\mu_{test}=0.01$ and variance is $\vartheta^2_{test}=1.05$. The dataset is taken from the GovDocs1 dataset and the Enron email dataset, which contain file and email data in a variety of formats. After preprocessing, the document fragment dataset is generated for training and testing. A total of 15695 normalized document fragment data were collected and divided into training and test sets in an 8:2 ratio. The GovDocs1 dataset contains document data in a variety of formats that are very common in electronic data forensics. The Enron email dataset contains a large amount of email data, which is also an important component of e-discovery. Both datasets are closely related to the e-discovery research focus. Furthermore, the GovDocs1 dataset and the Enron mail dataset comprise a plethora of heterogeneous document and email data, thereby enabling a comprehensive assessment of the model's efficacy in processing diverse and intricate forms of electronic data.

3.2 CNN-BiGRU-MHSA based file fragmentation detection model construction

After completing the construction and transformation of the file fragmentation dataset, the research will further combine MHSA mechanism, CNN, and BiGRU to build the file fragmentation detection model. BiGRU is a variant of recurrent neural networks specifically designed to process sequence data, especially time series or text data. It captures the information before and after the sequence through a bidirectional flow of information, which is crucial for understanding the context of file fragments. Transformer models typically require more computational resources. Especially, when using the self-attentive mechanism, its computational complexity increases with the length of the sequence. In contrast, file fragmentation detection involves capturing both local features (e.g., headers and tails) and global features (e.g., the overall structure of the file) of a file, and BiGRU is able to efficiently handle this type of data. Therefore, the study notated the final built detection model as CNN-BiGRU-MHSA, whose structure is shown in Figure 4.

In Figure 4, firstly, the preprocessed file fragments can be inputted into the model through the input layer, and the input file fragments have the size of N×512. Then, the embedding layer converts the input data into embedding vectors. Next, the CNN layer is introduced to extract local features and perform pooling. This is immediately followed by capturing the forward and backward temporal features of the file fragments using the BiGRU layer. Subsequently, the MHSA layer captures the hidden features through multiple attention heads as a way to enhance the feature extraction. The global average pooling layer (GAPL) pools the MHSA layer's output in order to minimize the feature dimensions. Meanwhile, to prevent overfitting, a dropout layer is added after the GAPL to randomly ignore some neuron outputs. Finally, the model contains two classification layers. Classification layer 1 outputs a dimension of N×64 and classification layer 2 outputs a dimension of N×20, which together constitute the final classification result. In the CNN-BiGRU-MHSA model, in an attempt to avoid the feature value gap being too large and thus affecting the extraction of features, it is necessary to perform a normalization operation on the input data [17]. The normalized formula is obtained by making the cleaned data feature r_{ij} as shown in Equation (2).

$$r'_{ij} = \frac{r_{ij} - r_{\min}}{r_{\max} - r_{\min}} \tag{2}$$

In Equation (2), r'_{ij} denotes the normalized $r_{\min}$, $r_{\min}$ and are the minimum and maximum values of the sample data. The set of normalized data is denoted as $s=[r_1, r_2, \cdots, r_n]$ and n is the individuals. According to Equation (2), the obtained s is used as an input to the CNN-BiGRU-MHSA model, which is first subjected to a convolution operation via CNN. The study chooses a 3×3

convolutional kernel for local feature extraction and used 64 filters to capture the features of the input data from different perspectives. Taking V_i in V_s as an example, the new features of V_i after convolution operation are obtained as shown in Equation (3) [18-20].

$$h_i = f\left(W_i * V_i + b\right) \tag{3}$$

In Equation (3), h_i denotes the new feature of V_i after convolutional processing. $f(\cdot)$ is the ReLU activation function (AF). b denotes the bias. W_i denotes the coefficients of the i th convolution kernel in V_i. A convolution kernel d is utilized to convolve all the features in V_s to obtain all the features at this point as shown in Equation (4).

$$H^d = \left[h_1^d, h_2^d, \cdots, h_i^d\right] \tag{4}$$

In Equation (4), H^d denotes the new features obtained after the convolution kernel d performs convolution operation on all the features in V_s. The H^d after convolution of all the convolution kernels of different sizes in the CNN is superimposed to obtain the output sequence (OS) of the final CNN, as shown in Equation (5).

$$H_s = \left[H^1, H^2, \cdots, H^d\right] \tag{5}$$

In Equation (5), H_s is the OS of the CNN. In BiGRU layer, the formula for reset gate is shown in Equation (6).

$$r_t = \sigma\left(W_r \cdot \left[h_{t-1}, x_t\right]\right) \tag{6}$$

In Equation (6), t denotes the moment. r_t is the output value (OV) of the reset gate under t moment. W_r denotes the weight matrix of the reset gate. x_t denotes the input under the t moment. h_{t-1} denotes the hidden state (HS) at the $t-1$ moment. σ denotes the sigmoid AF. The formula for the candidate HS is shown in Equation (7).

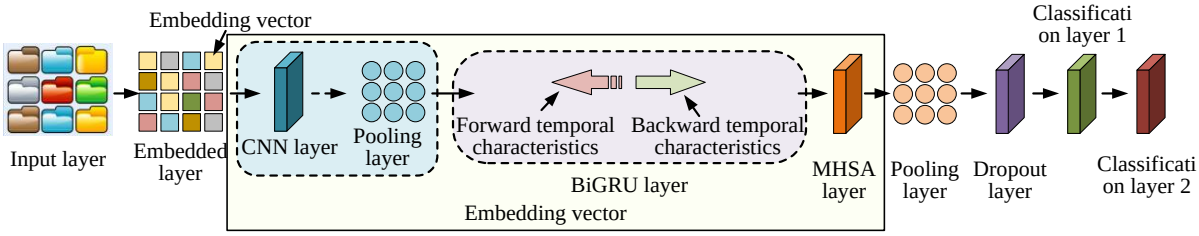


Figure 4: Structure diagram of CNN-BiGRU-MHSA model

$$h_t = \tanh\left(W_r \cdot \left[r_t * h_{t-1}, x_t\right]\right) \tag{7}$$

In Equation (7), h_t denotes the HS at the moment of t. The formula for updating the gate is shown in Equation (8).

$$z_t = \sigma\left(W_z \cdot \left[h_{t-1}, x_t\right]\right) \tag{8}$$

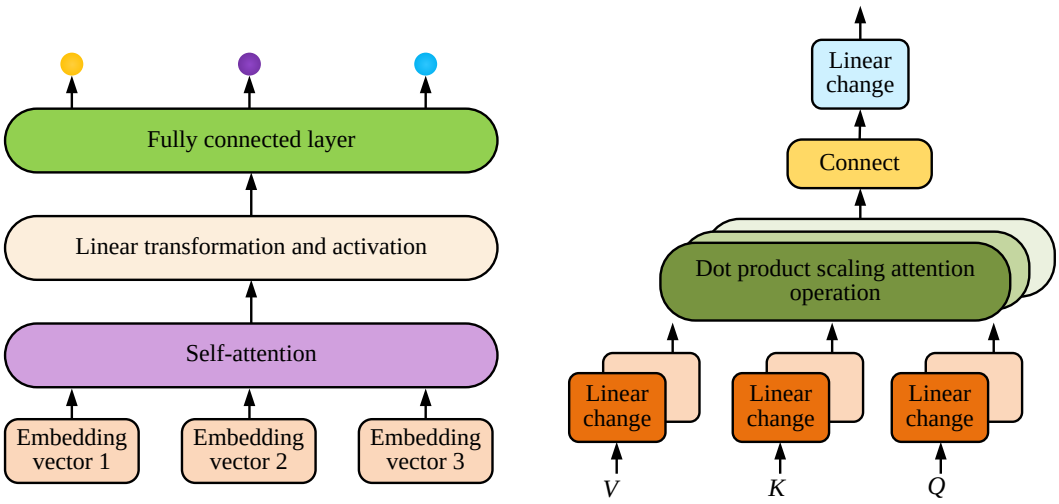
In Equation (8), z_t is the OV of the update gate (UG) at the t moment. W_z denotes the weight matrix of the UG. The formula for the HS under S moment is shown in Equation (9).

$$h_t = \left(1 - z_t\right) * h_{t-1} + z_t * h_t \tag{9}$$

In Equation (9), h_t is the HS at the t moment. In the MHSA layer, the adopted MHSM consists of a combination of SAM and multi-head attention mechanism (MHAM). This structure can enhance the model's ability to understand the input data by processing the data in parallel with multiple attention heads and learning features in different subspaces. The structure of SAM and MHAM is shown in Figure 5.

In Figure 5(a), SAM converts the input sequences into embedding vectors and then generates the weight matrix of query Q, key K, and value V. Next, the dot product of Q and K is computed and normalized by applying the Softmax function, and the resulting weights are used to weight and sum the V matrix and generate the self-attentive output. As shown in Figure 5(b), MHAM first linearly transforms the input sequence into multiple Q, K, and V matrices, respectively. Each attention head computes the attention output independently. The final multi-head attention output is then created by splicing and linearly transforming each head's outputs. The formula for generating multiple Q, K, and V matrices is shown in Equation (10).

$$\begin{cases} Q_m = W_{qm} X \\ K_m = W_{km} X \\ V_m = W_{vm} X \end{cases} \quad m = 1, 2, \cdots n \tag{10}$$



(a) Self-attention mechanism (b) Multi-head attention mechanism

Figure 5: SAM and MHAM structure diagram

In Equation (10), X denotes the embedding vector of the input sequence. Q_m, K_m, and V_m denote the query, key and value matrices of the m th header, respectively. W_{qm}, W_{km}. and W_{vm} denote the weight matrices of Q_m, K_m. and V_m, respectively. The attention OV of each head is shown in Equation (11).

$$\begin{aligned} head_m &= Attention\left(Q_m, K_m, V_m\right) \\ &= soft\max\left(\frac{Q_m K_m^T}{\sqrt{d_k}}\right)V_m \end{aligned} \tag{11}$$

In Equation (11), $head_m$ denotes the attention OV of the m th head. K_m^T denotes the transpose matrix of K_m. d_k denotes the dimension of the key vector, which is used to scale the dot product result. At the MHSA layer, the output process of splicing all the heads is shown in Equation (12).

$$\begin{aligned} &MultiHead\left(Q,K,V\right) \\ &= Concat\left(head_1, head_2, \cdots head_n\right)W_O \end{aligned} \tag{12}$$

In Equation (12), *Concat* denotes the splicing operation. W_O denotes the final output weight matrix. The operational flow of GAPL is shown in Figure 6.

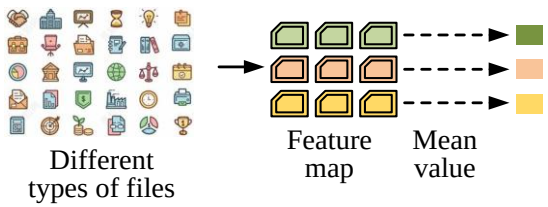


Figure 6: Schematic diagram of GAPL

In Figure 6, GAPL generates a smaller feature representation by averaging the pooling of all elements in each channel. This preserves important spatial information and reduces feature dimensions, thereby reducing computational complexity. The GAPL is characterized by the absence of learning parameters, which renders it an effective means of reducing the complexity of the model and the risk of overfitting. This is achieved while retaining the global information of the feature map, thereby enabling the model to capture a more expansive range of features. The flow of the Dropout operation is shown in Figure 7.

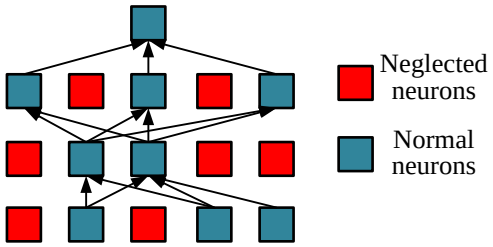


Figure 7: Dropout layer schematic diagram

In Figure 7, the dropout layer randomly ignores the outputs of a subset of neurons with a certain probability during the training process. That is, by setting the outputs of these neurons to zero, the model is better able to generalize and learn using different sub-networks for each training iteration. In the process of building the CNN-BiGRU-MHSA model, the study carefully parameterized the BiGRU and MHSA layers to optimize the feature extraction and classification performance of the model. The number of hidden layer units in the BiGRU layer is 256. The number of attention header bits in the MHSA layer is 8, and the dropout rate is set to 0.2.

4 Results

To demonstrate that the constructed CNN-BiGRU-MHSA model has better performance in the file fragmentation detection task, the study tests the baseline performance (BP) of the model and the effect of practical application respectively. LS-CNN, bidirectional long

short-term memory with conditional random fields (BiLSTM-CRF), and attention mechanism-recurrent neural network (AM-RNN) are selected as three comparison models. RNN as three comparison models. The performance of the four models is tested under the detection metrics such as loss function, accuracy, recall, and F1 value.

4.1 Baseline performance analysis of CNN-BiGRU-MHSA models

The experimental environment configuration used for the study includes an Intel Core i7-10700K processor with 32GB of RAM, an NVIDIA RTX 3080 graphics card, an Ubuntu 20.04 operating system, and the TensorFlow 2.5.0 DL framework. Figure 8 illustrates the comparison of the objective loss function and actual loss function trends for each of the four models.

The target loss function curves and actual loss function curves of AM-RNN, LS-CNN, BiLSTM-CRF, and CNN-BiGRU-MHSA are given in Figure 8, respectively. In Figure 8, the actual loss function curve of CNN-BiGRU-MHSA matches well with the target loss function curve throughout the iteration process. However, there are different degrees of ups and downs between the actual loss function curves and the target loss function curves of all three models, AM-RNN, LS-CNN, and BiLSTM-CRF, which do not match well. This illustrates that CNN-BiGRU-MHSA has better stability during the iterative process. The classification precision rate of the four models in different datasets is tested, as shown in Figure 9.

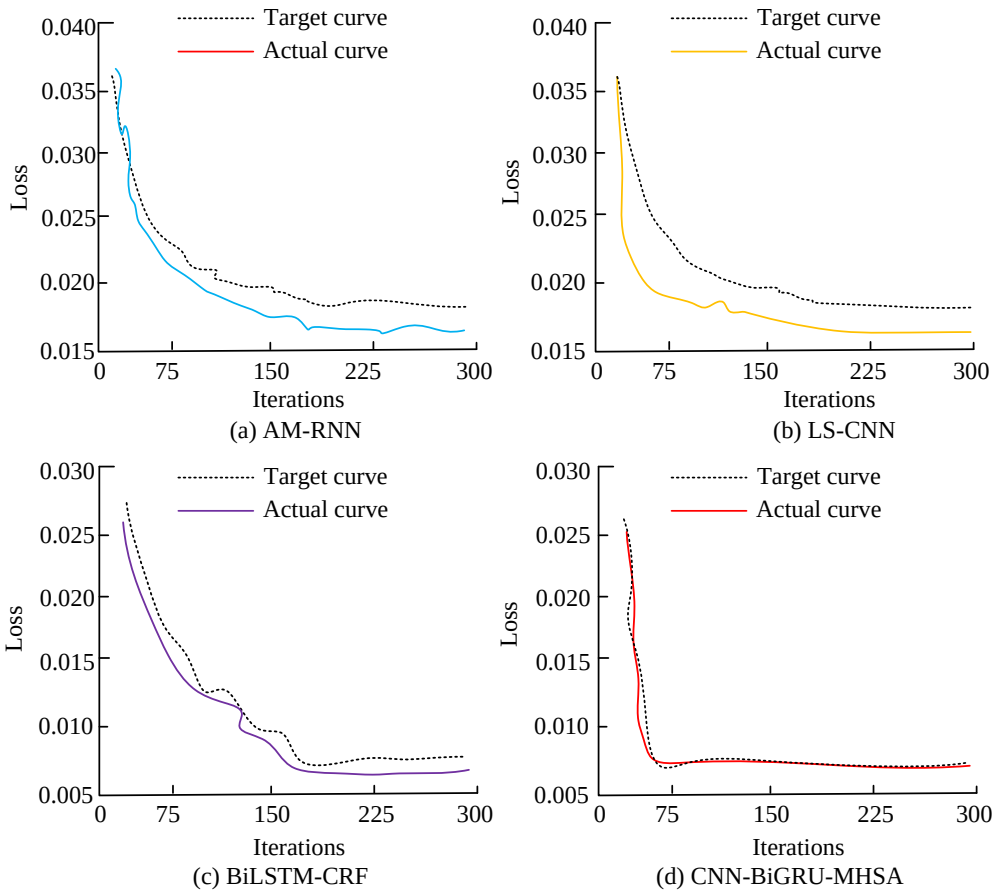


Figure 8: Loss curves for different models

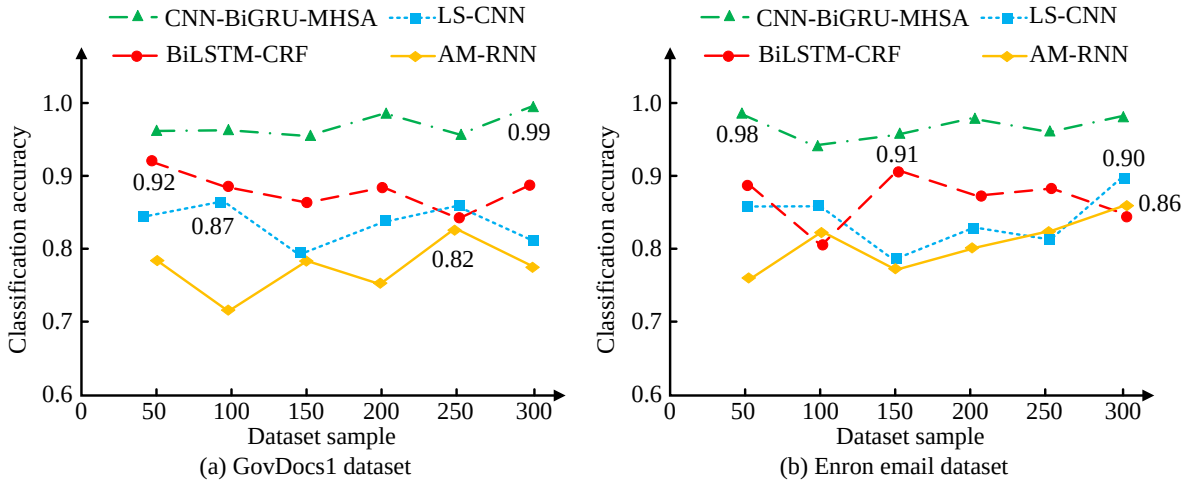


Figure 9: Classification precision rate of different models in two data sets

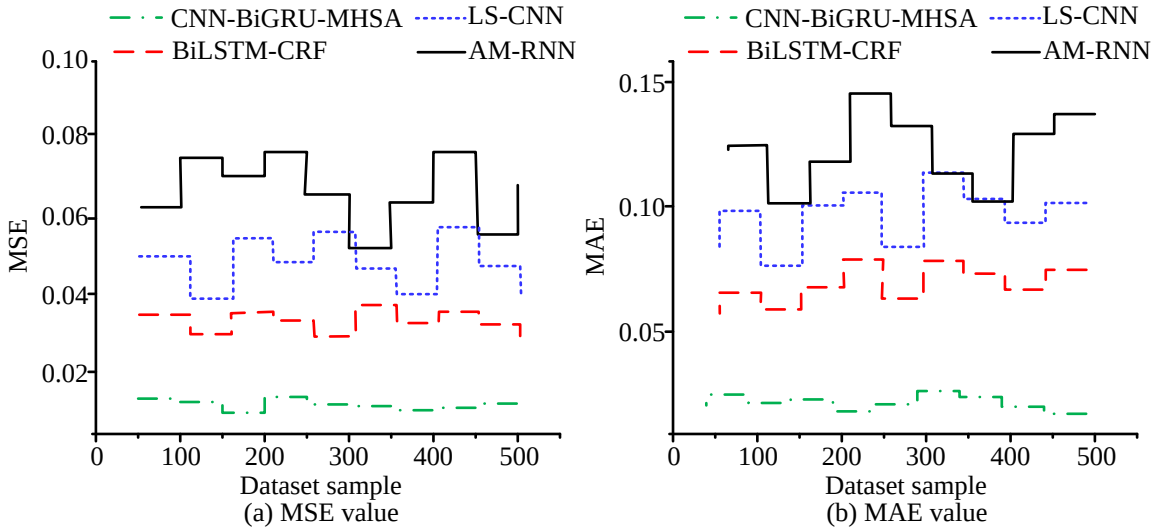


Figure 10: MSE and MAE for different models

Table 2: Statistical significance test results of different models

Data set	ANOVA		t-test		
	F-value	P-value	Model comparison	t-value	P-value
GovDocs1	5.89	0.00	CNN-BiGRU-MHSA vs AM-RNN	3.52	0.00
			CNN-BiGRU-MHSA vs LS-CNN	4.11	0.00
			CNN-BiGRU-MHSA vs BiLSTM-CRF	2.87	0.01
Enron email	6.23	0.00	CNN-BiGRU-MHSA vs AM-RNN	3.98	0.00
			CNN-BiGRU-MHSA vs LS-CNN	3.65	0.00
			CNN-BiGRU-MHSA vs BiLSTM-CRF	3.21	0.00

Table 3: Results of ablation experiment

CNN	BiGRU	MHSA	Average accuracy (%)
√	×	×	76.57
×	√	×	78.24
×	×	√	71.23
√	√	×	92.11
	√	√	91.59
√	×	√	93.77
√	√	√	98.97

Figure 9(a) and Figure 9(b) show the classification precision rate values of the four models in the GovDocs1 and Enron email dataset, respectively. In Figure 9(a), the maximum classification precision rate of AM-RNN, LS-CNN, BiLSTM-CRF, and CNN-BiGRU-MHSA in GovDocs1 dataset are 0.82, 0.87, 0.92, and 0.99, respectively, when the samples rising. Similarly, it can be obtained that in Figure 9(b), AM-RNN, LS-CNN,

BiLSTM-CRF and CNN-BiGRU-MHSA have maximum classification precision rate of 0.86, 0.90, 0.91, and 0.98 in the Enron email dataset dataset, respectively. In summary, the classification accuracies of CNN-BiGRU-MHSA in both datasets exceed 0.95, demonstrating the model's generally strong baseline classification performance. The mean square error (MSE) and mean absolute error (MAE) performances of the four models are tested, as shown in Figure 10.

Figures 10(a) and 10(b) show the MSE and MAE of AM-RNN, LS-CNN, BiLSTM-CRF, and CNN-BiGRU-MHSA, respectively, in the test set. The CNN-BiGRU-MHSA performs best in the error test, with the lowest MSE and MAE values of 0.08 and 0.12, respectively, which are much lower than that of the AM-RNN model in the MSE value of 0.53 and MAE value of 0.10. To verify the statistical significance of the performance differences between the models, t-test and analysis of variance (ANOVA) are further conducted. The specific results are shown in Table 2.

In Table 2, the classification performance of CNN-BiGRU-MHSA model on GovDocs1 and Enron mail data sets is statistically significant compared with other models, and the P values are all less than 0.05. This shows that the performance improvement of the CNN-BiGRU-MHSA model is remarkable. At the same time, it further verifies the superiority of CNN-BiGRU-MHSA model in classification performance. Finally, the ablation experiment is continued and the specific results are shown in Table 3.

Table 3 shows the average classification accuracy in two datasets under different combinations. It can be seen that the classification accuracy of CNN+BiGRU+MHSA is significantly better than other combinations. Among them, the classification accuracy of single MHSA is the lowest, while the accuracy of single BiGRU is significantly higher than that of MHSA and CNN. This may be because BiGRU has some ability in sequence modeling, but its performance is not as good as that of CNN when used alone. Overall, each component in the CNN-BiGRU-MHSA model contributes to improving the classification performance, especially when all three components are included, the performance of the model is the best. This shows that the CNN-BiGRU-MHSA model is reasonable and superior.

4.2 Application effect of CNN-BiGRU-MHSA modeling

To corroborate the CNN-BiGRU-MHSA model's superior classification performance in actual file fragmentation detection scenarios, the research employs a crawler tool to gather over 1,000 distinct categories of electronic data from an information website. It is also categorized into eight common file fragmentation types according to the classification rules in Figure 2. The crawler tool used for research is an automatic data collection program that can crawl the required data from the specified website according to the preset rules. The tool has the ability to automatically identify the site structure, extract files of specific formats and support multithreading operations. The selected information website is an online resource platform that provides various types of electronic documents and data files. The website is known for its rich data types and high data update frequency, which is suitable for the data collection needs of research. The rules are based on common file type and extension standards in electronic data forensics. Classification criteria include file extension, file header information, file content characteristics, etc. In the process of implementation, the file extension is initially utilized for preliminary classification, and subsequently, the file header information and content characteristics are integrated for detailed classification. This approach ensures the accuracy and integrity of the classification process. The classification effect of the four models for the eight file fragment types is tested, as shown in Figure 11.

Figure 11 give the classification accuracy and classification time of CNN-BiGRU-MHSA, BiLSTM-CRF, LS-CNN, and AM-RNN for detecting eight file fragment types, respectively. Among them, file types 1-file types 8 are (.txt), (.csv), (.doc), (.gif), (.xml), (.pdf), (.jpg), and (.html), respectively. In Figure 11, the CNN-BiGRU-MHSA model has the best classification accuracy and the shortest classification time. The highest classification accuracies of CNN-BiGRU-MHSA, BiLSTM-CRF, LS-CNN, and AM-RNN are 99.2%, 93.4%, 88.1%, and 86.9%, respectively. The shortest classification times are 0.09s, 0.38s, 0.56s, and 3.62s, respectively. The four models are further tested for the FDR for different document types, as shown in Table 4.

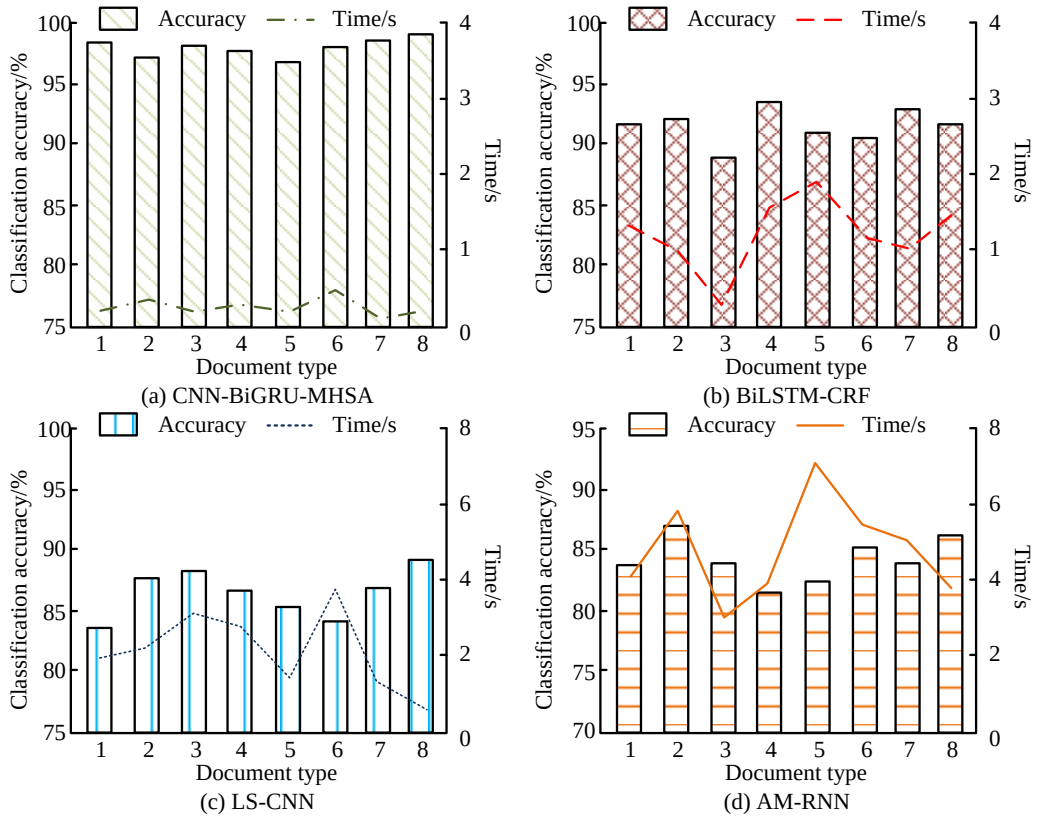


Figure 11: CA and classification time of different models

Table 4: FDR of four models in the process of file classification detection

File type	AM-RNN	LS-CNN	BiLSTM-CRF	CNN-BiGRU-MHSA
1	0.48%	0.28%	0.22%	0.06%
2	0.51%	0.32%	0.17%	0.11%
3	0.42%	0.20%	0.20%	0.08%
4	0.36%	0.25%	0.12%	0.02%
5	0.44%	0.31%	0.15%	0.10%
6	0.46%	0.24%	0.11%	0.05%
7	0.50%	0.29%	0.19%	0.13%
8	0.39%	0.33%	0.23%	0.11%

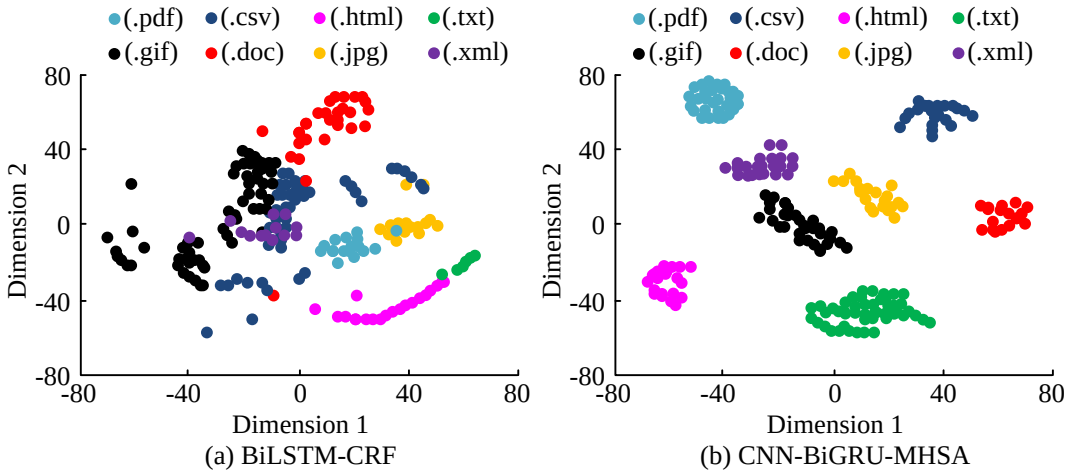


Figure 12: Classification results of file fragmentation of different models in the two models

The FDR is the proportion of all samples that are actually negative categories (i.e., not the category of interest to the study) that the model incorrectly predicts to be positive categories (i.e., the category of interest to the study.) The lower the FDR, the less the tendency of the model to misclassify negative categories as positive

categories. In Table 4, the lowest FDRs for the eight file types detected using CNN-BiGRU-MHSA, BiLSTM-CRF, LS-CNN, and AM-RNN are 0.02%, 0.11%, 0.24%, and 0.36%, respectively. The CNN-BiGRU-MHSA model's total FDR is significantly lower than the other three models when compared, staying around 0.15%. The classification effects of the four models are represented by clustering in the dimension space, as shown in Figure 11.

Figure 12(a) and 12(b) show the classification results of BiLSTM-CRF and CNN-BiGRU-MHSA for file fragments in dimensional space, respectively. Eight different types of file fragments are better classified in the CNN-BiGRU-MHSA model than the BiLSTM-CRF model. In Figure 12(b), the classification results of CNN-BiGRU-MHSA are neater and there are no misclassifications and omissions. However, in Figure 12(a), the classification of BiLSTM-CRF is more chaotic and misclassification of document fragments occurs. Overall, the proposed model is easier to identify text files (such as .txt and .csv) because such files usually have a consistent structure and format. For image files (such as .gif and .jpg), the model must rely on the binary pattern and visual characteristics of the files to distinguish them.

5 Discussion

The CNN-BiGRU-MHSA model proposed in the study performed exceptionally well on the task of detecting file fragmentation in electronic data forensics, significantly outperforming models such as AM-RNN, LS-CNN, and BiLSTM-CRF. The model achieved classification accuracy of 0.99 and 0.989 on the GovDocs1 and Enron email datasets, respectively. The model proposed in reference [6], based on graph attention networks and MHSA, demonstrated higher precision, recall, and F1 values on the drug-target interaction dataset. This indicated that the introduction of MHSA for fragmentation detection classification had a certain rationality. The LS-CNN model based on SAM proposed in reference [7] showed good classification reliability on NT data, but had limitations in utilizing multi-dimensional information. In contrast, the CNN-BiGRU-MHSA model proposed in this study combined CNN, BiGRU, and MHSA mechanisms to optimize feature extraction and sequence modeling. This combination not only overcome the limitations of traditional SAM in one-dimensional feature extraction, but also improved the model's detection and extraction efficiency for multi-dimensional features. The use of the MHSA mechanism was a significant innovation of the study. It processed data in parallel with multiple attention heads, improving the model's understanding of the input data, which was a novel approach in the field of electronic data forensics. Accurate detection of file fragmentation was critical for data recovery and evidence integrity. The high accuracy and low error rates of the model proposed in the study indicated that it could effectively improve the accuracy and efficiency of electronic data forensics.

6 Conclusion

A new method for detecting file fragments in electronic data forensics, the CNN-BiGRU-MHSA model, was proposed by this study. This model combined the advantages of CNN, BiGRU, and MHSA, and achieved excellent performance in classification accuracy and efficiency. The integration of these components allowed multi-dimensional features to be extracted more comprehensively, which overcome the limitations of traditional SAM. In practical application, the classification accuracy of this model reached 99.2%, and the FDR was only 0.02%, highlighting its potential to improve the effectiveness of electronic data forensics. The research results provided an accurate and efficient file fragment detection method for this field. This not only fills the gap in the existing technology, but also points out the direction for future research and practical application. Nevertheless, the proposed model still has room for improvement, especially when dealing with extremely complex and random file fragments. Future work will concentrate on further optimizing the model structure with the objective of enhancing its adaptability and robustness in the context of challenging situations.

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A Comparative Analysis of Extreme Gradient Boosting, Decision Tree, Support Vector Machines, and Random Forest Algorithm in Data Analysis of College Students' Psychological Health

Qiong Li[1,2*], Jian Zhou[3]
1School of Mathematics and Physics, Hubei Polytechnic University, Huangshi 435000, China
[2]Hubei Key Laboratory of Intelligent Convey Technology and Device (Hubei Polytechnic University), Huangshi 435000, China
[3]Wuhan Raycus Fiber Laser Technologies Co, LTD, Wuhan 430074, China
E-mail of corresponding author: liqiong872979454@163.com
[*]Corresponding author

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To solve the problem of identifying the mental health status of college students, this study investigated the psychological conditions of students in a certain department of a university in Hubei Province through a questionnaire survey using the SCL - 90 scale. It combined machine learning algorithms to analyze the applicability of the model and explore the differences between students with healthy and sub - healthy mental states. Data (including basic information) of 500 students were randomly collected. A self - compiled questionnaire was used in combination with on - site scoring by psychological teachers to classify the mental states of the 500 students into healthy and sub - healthy states. Questionnaire data were analyzed through decision tree, support vector machine, random forest, and XGBOOST algorithms to quickly identify the healthy and sub - healthy states and to mine the behavioral characteristics that have a certain correlation with the mental health status of students. The data information of 500 students was modeled respectively, and the classification effects of the models were evaluated through accuracy, precision, recall, F1 - score, and AUC. The results showed that among the four methods, the random forest had the best classification effect, with an R2 score of 0.8891, which was higher than the R2 score of 0.8393 for the decision tree, the R2 score of 0.8840 for the support vector machine, and the R2 score of 0.8618 for the XGBOOST algorithm. Considering the advantages of the random forest in terms of classification performance, modeling time, interpretability, feature selection, and simplicity, we recommend using the random forest model to assist in the diagnosis of mental health status classification. The experimental results on the SCL - 90 scale survey and the student basic information dataset show that the proposed model has high accuracy and can converge quickly, enabling more effective and accurate prediction of students' mental health status.

Povzetek: Primerjava učinkovitosti algoritmov strojnega učenja, kot so Extreme Gradient Boosting (XGBOOST), odločitveno drevo, podporni vektorski stroji (SVM) in naključni gozd, pri analizi psihološkega zdravja študentov. Uporablja podatke iz vprašalnika SCL-90 in ugotavlja, da naključni gozd dosega najboljše rezultate pri klasifikaciji mentalnega zdravja, s poudarkom na njegovi natančnosti, hitrosti in interpretaciji. Študija priporoča uporabo naključnega gozda za pomoč pri diagnozi mentalnega zdravja.

1 Introduction

The accuracy of psychological problem diagnosis and the effectiveness of intervention have always been major challenges in the field of mental health, largely due to the lack of scientific prediction tools [1-3]. With the increasing attention of the country and society to mental health issues, researchers are increasingly integrating modern scientific and technological methods (such as machine learning) into the research of mental health problems. As the core of artificial intelligence, machine learning has demonstrated unique advantages in many fields (such as finance and medicine), and the application of machine learning in the field of mental health is an inevitable trend.

Current research on mental health mainly focuses on two aspects. One is the text analysis and treatment of psychological problems, and the other is the analysis and prediction of influencing factors of mental health. For the first aspect of research, Ahmed et al. [4] proposed a deep adaptive clustering model based on an interpretable attention network based on the text descriptions of psychological patients. The experimental results showed that this method helps to label texts and improve the recognition rate of mental disorder symptoms. Li [5] designed a mental health education system based on

artificial intelligence online technology, which can conveniently and quickly query daily psychological problems according to the text description information of psychological patients and provide intelligent online psychological counseling to help patients overcome psychological problems. For the second aspect of research, Chen and Jiang [6] analyzed the influencing factors of mental health based on cognitive computing, combining the symptom self - assessment scale (SCL_90), social rating scale, and health cognition questionnaire (HCQ_127) test data of students from different regions in China and the United States. The research showed that students in developed regions are more likely to have psychological problems. Zhou [7] used the symptom self - assessment scale (SCL_90) data of 1,264 freshmen at Guizhou University in China and classified the mental health status of freshmen using the decision tree C4.5 algorithm. The classification results showed that somatization and hostility are important factors affecting students' mental health. Liu and Xu [8] applied a BP (BackPropagation) neural network to predict students' psychological problems based on students' psychological, personal basic information, and socioeconomic data. The experimental results showed that this method has a high prediction accuracy and can effectively predict students' psychological problems.

However, the accuracy of parameter estimation of traditional machine - learning models for psychological diagnosis often depends on a large sample size, which is not suitable for the small - sample situations that sometimes occur in reality. Therefore, in recent years, some researchers have proposed machine - learning methods that can extract key information from small samples for psychological diagnosis [9-10], and these methods have good robustness for various types of data, enabling relatively accurate classification. However, these studies have not compared different machine - learning methods, and previous studies have rarely involved the four machine - learning methods of decision tree, support vector machine, random forest, and XGBOOST algorithm. These methods each have their own advantages in simple classification tasks. For example, XGBOOST uses the gradient - boosting method, which can continuously optimize the model. At the same time, it has a built - in regularization term to effectively prevent over - fitting and supports parallel computing, with a fast-training speed. The learning process of the decision - tree model automatically extracts important features, and in the case of less data, it has an advantage over other complex models for simple classification problems, and the interpretation of the results does not require a mathematical background [11]. When dealing with non - linear problems, SVM is suitable for many features; it can handle the interaction of nonlinear features with strong generalization ability; and it is suitable for small samples. The random - forest algorithm, due to its method of using multiple trees for voting, has a good resistance to noise and can adapt to various data types. Therefore, this study intends to use four machine - learning methods (decision tree, support vector machine, random forest, and XGBOOST algorithm) to compare the prediction of mental health status by different machine - learning methods, fit the psychological diagnosis data of college students under samples of different sizes, study the impact of small samples on the prediction results of different machine - learning methods, and thus obtain the classification accuracy of different machine - learning methods under small samples. This provides an effective theoretical method for the application of psychological diagnosis and evaluation under small samples.

2 Methods

The dataset used in this paper is derived from a mental health questionnaire for students at a certain university in Hubei Province. To ensure satisfactory experimental results, data pre - processing operations are required. Data pre - processing includes methods such as data cleaning, data integration, data transformation, and data reduction. To guarantee the accuracy of the experimental results, data with incomplete scale responses are deleted, ensuring that the scale assessment results of the data used in the experiment are all complete responses. Also, multiple assessment data are removed to ensure that each subject in the dataset corresponds to only one assessment result. Association rule algorithms are used to discover the relationships between scale factors, screen frequent item sets and association rules, and perform data discretization on scale factor scores and scale scores. The basis for this is the scale's scoring criteria. Taking the SCL - 90 scale as an example, if the factor standard score is greater than 2 points, the factor is considered positive with symptoms; otherwise, it is negative without symptoms. In addition, data discretization is also required to assess the prediction accuracy of the model. The data required in this paper include scale scores and factor scores. Taking the SCL - 90 scale as an example, the screened dataset includes scale scores, somatization (SOM) factor scores, obsessive - compulsive symptoms (OBS) factor scores, interpersonal sensitivity (INT) factor scores, depression (DEP) factor scores, anxiety (ANX) factor scores, hostility (HOS) factor scores, phobia (PHO) factor scores, paranoid ideation (PAR) factor scores, psychoticism (PSY) factor scores, and other (MIS) factor scores. In this research, the psychological assessment scale is simplified from the perspective of reducing the number of scale item groups.

According to the needs of the experimental design, the data required for this experiment are selected from the dataset to form a new dataset. The new dataset includes the total scale score, scores of each factor, the label of the total score, and the labels of each factor. In the experimental part of this paper, factors are represented by their English abbreviations.

This research applies four classical machine - learning regression algorithms to predict scale scores, including decision tree, support vector machine, random forest, and XGBOOST algorithm. By comparing the performance of scale - score prediction models based on

these four classical algorithms, the optimal algorithm is selected.

In the experiments of this paper, to avoid the adverse effects of a small number of training samples on the model and the impact caused by the random division of the training set and the test set, the five - fold cross - validation method is adopted. This method reduces the impact of randomness on the model performance and ensures the stability and accuracy of the prediction results. The method divides the dataset into five equal parts. Each time, four of these parts are used as the training set, and the remaining one part is used as the validation set. Model training is carried out five times, and the model evaluation indicators of the five experiments are obtained. Finally, the average value of the five model evaluation indicators is returned as the model evaluation index. The entire sample is trained using the four algorithms, and appropriate parameters are selected through the cross - validation method to establish the optimal model. Finally, the model is verified and analyzed according to the mental health diagnosis results. The experimental results show that the mental health status assessment method based on the random forest can achieve an average accuracy of 96.67%, which can effectively diagnose the mental health status of college students.

2.1 Decision tree algorithm

The decision tree algorithm (DT) is a method for approximating discrete function values. It is a typical classification method. First, it processes the data, uses an inductive algorithm to generate readable rules and a decision tree, and then uses the decision to analyze new data. Essentially, the decision tree is a process of classifying data through a series of rules. The decision - tree algorithm constructs a decision tree to discover the classification rules contained in the data. How to construct a decision tree with high accuracy and small scale is the core content of the decision - tree algorithm. The construction of the decision tree can be carried out in two steps. The first step is the generation of the decision tree: the process of generating a decision tree from the training sample set. The second step is the pruning of the decision tree: The pruning of the decision tree is a process of testing, correcting, and modifying the decision tree generated in the previous stage. Mainly, the data in the new sample dataset (referred to as the test dataset) is used to verify the preliminary rules generated in the process of decision - tree generation, and the branches that affect the prediction accuracy are removed. Compared with Logistic Regression, the decision - tree model can make a non - linear segmentation of the dataset well. At the same time, the tree - shaped model is closer to the human way of thinking, generates visual classification rules, and the generated model is interpretable, which can solve the classification problem of complex decision boundaries. As a typical machine - learning method, trees reflect a mapping relationship between object attributes and object values, and are not affected by the empirical distribution assumptions of the dataset itself.

2.2 Support vector machine

The support vector machine (SVM) is a machine - learning method based on statistical learning theory, mainly used for classification and regression analysis. Its core idea is to find an optimal hyperplane to separate samples of different classes and maximize the margin between the two classes. The basic principle of the support vector machine is to map the data into a high - dimensional space and construct an optimal hyperplane to achieve efficient data classification. Its core idea is to maximize the classification margin, so that data points of different classes are as far away from the decision boundary as possible, thereby improving the generalization ability of the classifier. In the case of linear separability, SVM finds the optimal hyperplane by solving a quadratic programming problem. In the case of non - linear separability, SVM maps the data into a high - dimensional space by introducing a kernel function to make it linearly separable.

2.3 Random forest

The random forest (RF) adopts the idea of ensemble learning, using multiple decision trees as weak classifiers, and then combines them through a certain strategy to form a strong classifier with better results. It generates multiple decision trees by randomly selecting some variables and data, and then aggregates the results of multiple decision trees through the voting method of the decision trees in the forest. Compared with the single judgment of a single decision tree, the random forest has higher accuracy, and this algorithm has very good stability. As a type of probabilistic graphical model, it represents the relationships between observed variables, predictive variables, and labels in an intuitive and easy - to - understand tree - diagram model. Each node branch represents the process of a parent node splitting into child nodes, and each path from the root node to the leaf node is an accurate description of a decision rule. As the number of base learners in the random forest increases, the random forest often converges to a lower generalization error. At the same time, different from the decision tree in Bagging, which selects the optimal splitting attribute from all attribute sets, the random forest only selects the splitting attribute from a subset of the attribute set, so the training efficiency is higher.

2.4 XGBoost

Ensemble learning is an effective strategy that combines multiple machine - learning algorithms. A single machine - learning algorithm can solve only limited problems and has poor generalization and application ability. However, combining multiple machine - learning algorithms to complete a certain learning task often produces better results. Each learner can be regarded as a basic learning unit, and through their combination, a powerful whole is finally integrated, which can be used to solve more complex problems.

Ensemble learning has advantages such as improving model performance, reducing overfitting, reducing variance, providing higher prediction accuracy, and handling linear and non - linear data. The extreme gradient boosting algorithm (XGBoost) uses multi - threading to accelerate the construction of trees, uses tree models as basic classifiers to form a powerful classifier, and integrates multiple basic classifiers together. This has the advantages of high efficiency, accuracy, and good interpretability in classification tasks.

The characteristics and comparison of the four classical machine-learning algorithms of decision tree, support vector machine, random forest, and ensemble learning are shown in Table 1.

Table 1: The characteristics and comparison of the four classical machine-learning algorithms

Algorithm	Advantages and Disadvantages
Decision Tree	Advantages: (1) The calculation is simple, and the results can be interpreted and visualized. (2) It is not sensitive to missing values. (3) It can handle irrelevant features. Disadvantages: (1) There may be an overfitting problem. (2) It performs poorly when dealing with highly correlated features. (3) It is difficult to handle continuous data.
Support Vector Machine	Advantages: (1) Applicable to a variety of features. (2) Capable of handling the interactions of non - linear features and has relatively strong generalization ability. (3) Suitable for small - sample data. Disadvantages: (1) Not suitable for large - sample data. (2) Sensitive to missing data.
Random Forest	Advantages: (1) Strong generalization ability. (2) Applicable to various features. (3) Insensitive to missing values and capable of handling imbalanced data. Disadvantages: (1) Not very effective when solving regression problems. (2) Low performance when there is a large amount of noise.
XGBoost	Advantages: (1) It adopts the gradient boosting method, which can continuously optimize the model. (2) It has a built - in regularization term, which can effectively prevent overfitting. (3) It supports parallel computing, resulting in a fast training speed. Disadvantages: (1) It has poor interpretability. (2) If the parameters are not set appropriately, the model may become too complex and lead to overfitting. (3) It has a high memory footprint. (4) It does not support real - time prediction.

3 Experiments

3.1 Data

From January to December 2023, the mental health situation of students in a university in Hubei Province was investigated. The results of 500 valid questionnaires were studied. Among the 500 students, 238 were confirmed to have mental sub - health and 262 were confirmed to have good mental health by the psychological counseling center. Based on these data, follow - up modeling and analysis research were carried out.

3.1.1 Investigation on influencing factors of college students' mental health

The survey tools are as follows:

(1) Self made questionnaire. There are 14 factors in total, including gender (male and female), grade (freshman, sophomore, junior and senior), subject (liberal arts and Science), place of origin (rural and urban), only child (yes or no), parental rearing style (democratic, authoritarian, doting and neglecting), parents' education level (primary school and below, middle school and high school, University and above), love (yes or no), weekly exercise time (0-2 hours, 2-5 hours, and more than 5 hours), family economic health (poor, average, and good), community activities (never, rarely, generally, and often), whether to fail the course (no, yes), whether to experience recent stress events (no, yes), and whether the family is single parent (yes, no). If the number of item options is n, the score will be 1 to n, for example, 0-2 hours, 2-5 hours and more than 5 hours of exercise per week will be scored as 1, 2 and 3 respectively. Each record is allowed to have at most 2 missing values. Otherwise, as invalid data, the missing values are filled with mode.

(2) Communication ability score. The professional psychological counseling room scores the students' communication ability by communicating with each student for three to five minutes, and then includes the communication ability as one of the analysis data of the students' overall psychological situation.

3.1.2 Investigation on college students' mental health

The Symptom Checklist 90 (SCL - 90) test was used, with scores of 0 (none); 1 (very light); 2 (moderate); 3 (heavier); 4 (severe). The scoring method involves statistical analysis of the main indicators and factor data. The overall evaluation of the mental health status of college students in this school is based on the screening criteria: a total score greater than 160 points, a positive number of items greater than 43, or any factor score greater than 2 points.

3.2 Experimental scheme

In the experiment, 80% (400) of the mental health data of the 500 college students were randomly selected as training samples, and 20% (100) of the data were selected as test samples. Taking R2 as the index, the gridsearchcv function was used to search for parameters such as learning_rate, n_iterations, and Max_Depth (the maximum depth of the tree) to find the best model. The main function of the gridsearchcv function is to automatically adjust parameters, specify the parameter range, and find the optimal result and its corresponding parameters, which is suitable for small datasets. By repeatedly changing the sample data and setting the parameter range, the final parameters were determined.

The experimental evaluation indicators include accuracy (a), precision (p), recall (r), F1 - score (F1), and the area under the receiver operating characteristic (ROC) curve (AUC) to evaluate the performance of the machine - learning model.

4 Experimental results

4.1 Performance comparison and verification of multiple algorithms

In the research on the mental health prediction model for college students in this paper, prediction models were established using random forest, XGBoost, decision tree, and SVM algorithms respectively. The gridsearchcv function was used to optimize the parameters of the decision tree and the other three methods. In each experiment, 80% of the total samples were randomly selected for training and 20% for testing. The prediction performance was quantified and ranked using accuracy, precision, recall, F - score, and AUC. The experimental results are shown in Table 2. By comparing the performance of different algorithms, the algorithm most suitable for a specific psychological assessment can be determined, thereby improving the accuracy and reliability of the assessment.

Table 2: Experimental results and comparisons of the four models

Methods	Accuracy	Precision	Recall	F1	AUC
DT	0.9533	0.9740	0.9375	0.9554	0.9923
SVM	0.9605	0.9625	0.9625	0.9625	0.9528
RF	0.9733	0.9871	0.9625	0.9746	0.9973
XGBoost	0.9666	0.9870	0.9524	0.9681	0.9957

As can be seen from Table 2, the random forest model achieved the best results among the four evaluation indicators. Its accuracy in predicting the mental health status of students is 0.97, the precision is 0.98, and the AUC is 0.996. While the decision tree model performed the worst, with values of 0.96, 0.96, and 0.95 respectively. According to the feature importance of the random forest model, the features affecting mental health are ranked as shown in Figure 1.

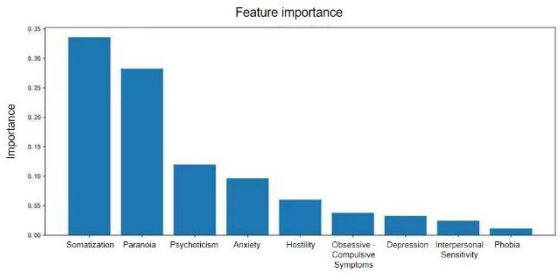


Figure 1: Feature importance ranking

The classification results showed that somatization, paranoia and psychoticism are important factors affecting students' mental health.

Using statistical methods, based on the proportion of the number of students with sub - mental - health in each group of susceptible factors, the important susceptible factors affecting college students' mental health are ranked as follows: parents' education mode; whether to experience recent stress events; communication ability score; grade; love; family economic status; whether the family is a single - parent family; only child; weekly exercise time; whether to fail a course; ,parents' education level; community activities; place of origin; gender; subject. This provides decision - making support for the formulation of college students' mental health training strategies.

The characteristics related to the family environment are: parents' education mode, family economic status, whether the family is a single - parent family, and whether the student is an only child. Their importance are ranked first, sixth, seventh, and eighth respectively, indicating that the family environment has a significant impact on the mental health of college students. Relevant educators can timely understand the changes in students' family environment by establishing an effective mechanism for regular family contact. Other important factors are: whether to experience recent stress events, communication ability, grade, love situation, weekly exercise time, and community activities. Therefore, encouraging students to participate in sports, cultivating a good learning atmosphere, and various community activities is conducive to the cultivation of college students' mental health. Grade is ranked fourth, indicating that as college students grow, their mental state constantly changes, demonstrating the dynamic nature of college students' mental health. Hence, regularly implementing mental health education is essential to ensure that this change is in the direction of improving mental health.

4.2 Model comparison in the case of small samples

The number of samples was reduced to 100, 150, and 200. The simulated data was still divided into training and test sets using 5 - fold cross - validation. The experimental results of Xgboost, decision tree, SVM (Support Vector Machines), and random forest on small samples were compared (see Table 3). The results show that the random forest model still achieved the best results in the four evaluation indicators of accuracy, precision, recall, and F1 - score. This indicates that the random forest model can more effectively predict the mental health status of students based on the SCL - 90 scale, helping schools to promptly identify students with psychological problems and carry out relevant interventions and counseling, enabling them to return to normal life and study, which has certain practical significance.

Table 3: Comparison of the effects of machine learning methods in the case of small samples

Algorithm	Sample size	Accuracy	Precision	Recall	F1	AUC
Decision Tree	100	0.9	0.8333	1	0.9091	0.9
	150	0.9556	0.9167	1	0.9565	0.9565
	200	0.95	0.9697	0.9412	0.9552	0.9514
Support Vector Machine	100	0.9667	0.9375	1	0.9677	1
	150	0.9778	0.9565	1	0.9778	0.998
	200	0.9833	1	0.9706	0.9851	0.9989
Random Forest	100	0.9333	0.8824	1	0.9375	0.9889
	150	0.9556	0.9167	1	0.9565	0.998
	200	0.9833	1	0.9706	0.9851	0.9989
XGBoost	100	0.9333	0.9333	0.9333	0.9333	0.9956
	150	0.9556	0.9167	1	0.9565	1
	200	0.9667	0.9706	0.9706	0.9706	0.9989

5 Discussion and suggestions

The research results show that:

The various indicators of Xgboost, decision tree, SVM (Support Vector Machines), and random forest are very similar and the scores are relatively high. This indicates that these models all fit the data well and can be considered as model options. Overall, the random forest model has a slightly higher score, showing the best scoring performance.

The classification accuracy of machine learning methods is not significantly affected by the sample size. The decision tree model performs poorly in classifying data, while the other models perform well.

In small - sample simulated data, the random forest algorithm and the support vector machine show good classification accuracy. The random forest algorithm exceeds the model with a sample size of 500 when the sample size is 200.

In actual small - sample psychological health diagnosis, it is recommended to use the support vector machine and the random forest algorithm, but the total number of attributes is required to be small. Through this research, the following conclusions can be drawn: Machine learning algorithms can provide rapid, consistent, and unbiased evaluations. Model algorithms can identify risk factors and predict outcomes, facilitating early intervention and prevention. They can also help customize treatment plans and optimize treatment effects.

From the comparative analysis of the performance of the four models in Table 2 and Table 3, it can be seen that the random forest model performs the best overall. The reasons are as follows:

(1). Reducing the impact of outliers: By constructing multiple decision trees and taking the average or majority - voting results, the random forest can effectively reduce the impact of individual outliers on the overall prediction results. In contrast, decision trees are prone to overfitting with relatively low prediction accuracy. The random forest greatly improves the model performance by integrating multiple decision trees.

(2). Reducing the risk of overfitting: Since the random forest uses a part of the samples and features to construct each decision tree, it reduces the possibility of overfitting, enabling the model to have better generalization ability. The random forest can handle thousands of input variables, determine the most important variables, and has strong processing ability for high - dimensional data. Therefore, it is considered a good dimensionality reduction method.

(3). Parallelization and distributed implementation: The highly parallel nature of the random forest makes it easy to implement in a distributed manner, which is very beneficial for large - scale data processing. When dealing with non - linear problems, SVM needs to select an appropriate kernel function, which has a high computational complexity and a slow training speed on large - scale data. The random forest performs better in handling high - dimensional features.

(4). Providing feature importance: The random forest can output the importance degree of features, which is very helpful for understanding and analyzing data features.

Therefore, the random forest shows certain advantages over decision trees and SVM in many aspects. However, in practical applications, the choice of which algorithm still needs to be determined according to the characteristics of specific problems and datasets.

This study also fits the psychological diagnostic data under small samples, and compares the prediction of results by different machine - learning methods, so as to explore the classification accuracy of different machine - learning methods under small samples. Although this study has examined the following aspects: (1) Explore the susceptible factors that affect the mental health level of college students with positive psychological symptoms; (2) Explore the effectiveness of machine - learning - based modeling in identifying and predicting college students with potential psychological problems; (3) Apply the effectiveness and accuracy of each machine - learning model in simulated small - sample data., limitations and directions of improvement are as follows: (1) The research objects are limited to a certain university in Hubei Province, so the sample representativeness is limited. (2) The predictive variables (susceptible factors) of the model in this study are measured by self - rating scales. Research shows that certain physiological susceptible factors also have a certain predictive effect on mental health. In the future, physiological indicators can be added to establish a prediction model to improve the accuracy of the model and provide more powerful auxiliary tools for the clinical work of college students' psychological health.

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Integrating Attention Mechanisms and ResNet-50 For Enhanced Driver Sleepiness Detection

Zhen Huang
Logic, Marxism Institute of Chongqing Normal University, Chongqing, 400000, China
E-mail: huang207885@163.com

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One of the main causes of traffic accidents is driver exhaustion, making the development of advanced systems crucial for real-time monitoring and preventive measures. This work presents a novel framework for intelligent information aggregation, enhancing decision-making in sleepiness detection by leveraging attention mechanisms and ResNet-50, a state-of-the-art deep convolutional neural network. The proposed system reliably classifies driver states by integrating logical inference with visual data elements such as head movements, eye closure patterns, and face recognition Experimental evaluations on the Driver Drowsiness Dataset (DDD) demonstrate the model's effectiveness, achieving an accuracy of 93.5%, a precision of 94.2%, a recall of 92.7%, and an F1-score of 93.4% These results highlight the synergy between artificial intelligence and attention mechanisms in improving classification performance. This research provides a robust and scalable foundation for AI-driven decision-making, contributing to safer and more intelligent transportation systems

Povzetek: Predstavljen je nov okvir za zaznavanje zaspanosti voznika, ki združuje mehanizme pozornosti in ResNet-50. Model analizira vizualne podatke, kot so premiki glave in zapiranje oči.

1 Introduction

The intelligent systems need that can solve problems in the real world has increased dramatically as a result of technological breakthroughs. Driver sleepiness detection is one such key application that has a direct bearing on transportation safety [1]. solutions that can precisely detect and categorize driver situations in real time are necessary since fatigue induced accidents continue to be a global concern. Creating such intelligent systems requires tackling the challenges of converting diverse data sources like head movements, eye closure patterns, and face landmarks into useful insights [2]. To ensure trust worthy information aggregation, this endeavor necessitates strong procedures that blend sophisticated computational tools with organized reasoning [3]. In this work, we propose a novel framework that combines logic and artificial intelligence to improving driver sleep detection and decision-making. We check visual data to find patterns suggestive of tiredness by utilize the ResNet-50 model, a potent deep convolution al neural network renowned for its exceptional feature extraction capabilities [4]. never the less, our method uses attention approach to compile data in an organized and understandable way rather than depending only on unprocessed AI predictions. The system can produce more accurate and dependable decisions [5][6]. we organize this paper into the following sections to give a clear understanding of our work. literature review, discussing related works; methodology, detail of the proposed framework; results, presenting experimental findings; Conclusion, summarizing contributions; and acknowledgment, expressing gratitude.

1.1 Motivation and challenges

its more importance in preventing traffic accidents, driver sleeping detection has been the subject of much research. Conventional techniques frequently depend on visual hint like Facial postures and eyes closures or physiological indications like Electroencephalography (EEG) and ECG [7]. however these methods are somewhat successful, they have drawbacks such the requirement for specialized sensors, their vulnerability to external influences, and their lack of flexibility [8]. The main difficulty is combining data from several sources into a cohesive system that can make decisions regarding the driver's condition in a changing environment[6]. these issues must be resolved while preserving scalability and real-time operability in a solid solution [9].

1.2 The role of logic and artificial intelligence in information aggregation

with deep learning models like ResNet-50 performing exceptionally well in tasks like image classification and feature extraction, artificial intelligence has completely transformed the field of driver monitoring [10]. But AI systems frequently function as ”black boxes,” their interoperability and capacity to integrate domain knowledge are con-

strained. contrarily, logic provides an organized method of reasoning, which makes it perfect for combining disparate data sources into a coherent decision-making procedure [11]. Our work guarantees accurate information aggregation that is both interpretable and scalable across a variety of use cases by fusing the advantages of artificial intelligence and attention-base reasoning [12].

1.3 A logical proposed framework contributions

This work presents a novel approach to identify and categorize driver drowsiness by combining attention-base inference techniques with ResNet-50's feature extraction capabilities. The following are the main contributions:

1. Creation of a hybrid framework that uses logic for organized reasoning and artificial intelligence for visual data processing Fig1.
2. Logical rules are included to improve the interpretability of AI-driven judgments and enable reliable information aggregation Fig1.
3. The Driver Drowsiness Dataset (DDD) was used to validate the suggested framework, showing notable gains in scalability, accuracy, and dependability 1.

2 Related work

The challenge of detecting driver drowsiness has been widely explored, leveraging advancements in artificial intelligence (AI), computer vision, and physiological monitoring systems. This section reviews prior approaches and methodologies, focusing on their advantages, limitations, and relevance to our proposed framework.

2.1 Visual-based approaches

Several studies have relied on visual cues such as facial expressions, eye closure patterns, and head movements to detect signs of fatigue. Deep learning models, such as convolutional neural networks (CNNs), have shown remarkable success in extracting visual features [4]. For instance, systems using the ResNet architecture have demonstrated robust performance in tasks involving facial landmark analysis [13]. However, these methods often face challenges related to occlusion, varying lighting conditions, and individual variability, which can compromise their reliability in real-world scenarios.

2.2 Physiological signal-based approaches

Physiological signals like electroencephalography (EEG), electrocardiography (ECG), and pulse rate have been widely used for drowsiness detection. These approaches are considered more accurate as they directly measure the driver's internal state [14]. However, their dependency on specialized sensors and susceptibility to noise from external factors limits their practical application in dynamic environments like driving [8].

2.3 Attention mechanisms in driver monitoring

Attention mechanisms have recently emerged as a powerful tool for improving feature extraction and refining model focus on critical aspects of input data. By dynamically assigning higher weights to significant features, attention modules enhance the detection of relevant patterns associated with driver drowsiness [15]. Recent studies have demonstrated that integrating attention mechanisms with deep architectures such as ResNet-50 improves robustness in complex scenarios, including low-light conditions and occlusions [16] [17]. Furthermore, attention-based models have been successfully employed in multimodal driver monitoring systems, where physiological signals such as heart rate variability and eye-tracking data are fused with visual information to enhance prediction accuracy [18]. This fusion enables a more adaptive and context-aware decision-making process, reducing false alarms and improving real-time applicability. By filtering out irrelevant noise and emphasizing subtle fatigue-related cues, attention mechanisms contribute significantly to the advancement of intelligent driver monitoring systems

2.4 Hybrid approaches

Recent efforts have aimed to combine visual and physiological data for enhanced robustness and accuracy. Hybrid models utilize multimodal data to compensate for the weaknesses of individual modalities. For instance, frameworks integrating facial landmarks with EEG signals have demonstrated improved performance [19]. However, these systems often encounter challenges related to synchronization, computational complexity, and real-time operability.

2.5 Role of AI in driver monitoring

Deep learning has revolutionized driver monitoring by enabling accurate feature extraction and real-time decision-making. Models such as ResNet-50 have been extensively used for image classification tasks, including driver state analysis [10]. The integration of attention mechanisms further enhances these models by focusing computational resources on the most critical regions of input data [20]. This combination addresses the limitations of conventional methods by improving both accuracy and interpretability. While significant progress has been made in driver drowsiness detection, existing approaches often struggle with issues related to reliability, scalability, and real-time functionality. The application of attention mechanisms within ResNet-50 addresses these challenges by offering a robust framework for feature extraction and prioritization. Moreover, the use of the Driver Drowsiness Dataset (DDD) for

validation ensures the practical applicability of the proposed solution.

3 Methodoloogy

The goal to improve decision-making, the methodology used in the present research aims to integrate attention mechanisms for information aggregation with artificial intelligence (AI) techniques. The study's main components are the application of the ResNet50 model, [1] a deep learning architecture well-known for its capacity to identify intricate features and patterns in data, and the Driver Drowsiness Dataset (DDD), an extensive dataset comprising drivers' physiological and image data. Through the integration of several data modalities and attention-base decision making, the objective is to create a system that can identify drowsy driving [7]. This system might then be expanded to real-time safety applications.

3.1 Dataset description and pre-processing

Images of people in cars mimicking "drowsy" and "awake" face postures make up the Driver Drowsiness Dataset (DDD). It's a useful tool for creating computer vision models that identify driver fatigue, a serious safety issue.

3.1.1 Driver drowsiness dataset (DDD)

An essential source of data for this research is the Driver Drowsiness Dataset (DDD)[21] [14]. It offers multi-modal data that is perfect for combining attention mechanism with artificial intelligence. The information includes physiological indicators like heart rate and eye movement patterns in addition to picture data taken by a camera trained on the driver's face. Finding out if the driver is aware or showing symptoms of drowsiness which could result in risky driving behavior is the main objective of this data.

Image Data Captures visual features of the driver's face, focusing on the eyes and facial expressions RGB Images (224x224 pixels)

Physiological Data Includes heart rate variability, blink rate, eye movement speed, and head orientation Numerical (continuous)

Labels Binary classification: 'Alert' (0) vs. 'Drowsy' (1) Binary (0/1)

3.1.2 Data pre-processing

Pre-processing is carried out in a number of ways to make sure the data is prepared for efficient analysis. The purpose of these procedures is to get the data ready for the ResNet50 model[5], which needs particular input formats and data circumstances in order to function at its best.

Image Normalization Each image is scaled in accordance with the ResNet50 model's set input size of 224x224 pixels. furthermore, to guarantee data homogeneity and promote more seamless training, pixel values are standardized to a range of 0 to 1.

Data Augmentation Techniques like random rotations, flipping, and zooming are used to enhance model generalization and further avoid overfitting. By doing this, the dataset becomes more diverse and replicates the variances in driving situations found in the actual world.

Feature Scaling To ensure that every feature contributes equally to the model's learning process, physiological data, such as heart rate and blink rate, are standardized to the range 0 and 1.

Label Encoding The binary labels "Drowsy" and "Alert" are appropriate for binary classification since they are encoded as 0 (Alert) and 1 (Drowsy)

3.2 Model evaluation

The process of selecting the best model from a group of potential models using factors like interoperability, parsimony, and forecast accuracy is known as model selection. too better for aggregation, intelligent information and decision making in computer vision and beyond[22].

3.2.1 Justification of ResNet50 utilization

Considering its strong design and track record of success in challenging picture classification tasks, the ResNet50 model was chosen for this investigation. Because ResNet50 can handle deep designs without experiencing the vanishing gradient problem, it is especially well suited for our methodology[23]. The model may retain training efficiency while learning deeper features by utilizing residual connections[24].

The 50 layers that make up ResNet50 are organized into blocks called residual blocks[25]. Particularly for extensive and complex data sets like pictures of driver faces, these blocks aid the model in remembering and transmitting information between layers, enabling more effective learning. The architecture of ResNet50 can be summarized as Fig.1

The skip connection helps the model avoid the degradation issue that comes with deeper networks by adding the input directly to the block's output within the residual block. The output is equal to:

$$Results = F(x, \{W_i\}) + x \tag{1}$$

where x is the block's input and $F(x, \{W_i\})$ is the residual mapping function. This architecture makes sure that deep features can be learned effectively and that information aggregation across layers stays seamless.

3.2.2 Model fine-tuning and integration

In this investigation, the pre-trained ResNet50 model is adjusted. We apply transfer learning by adjusting the model's

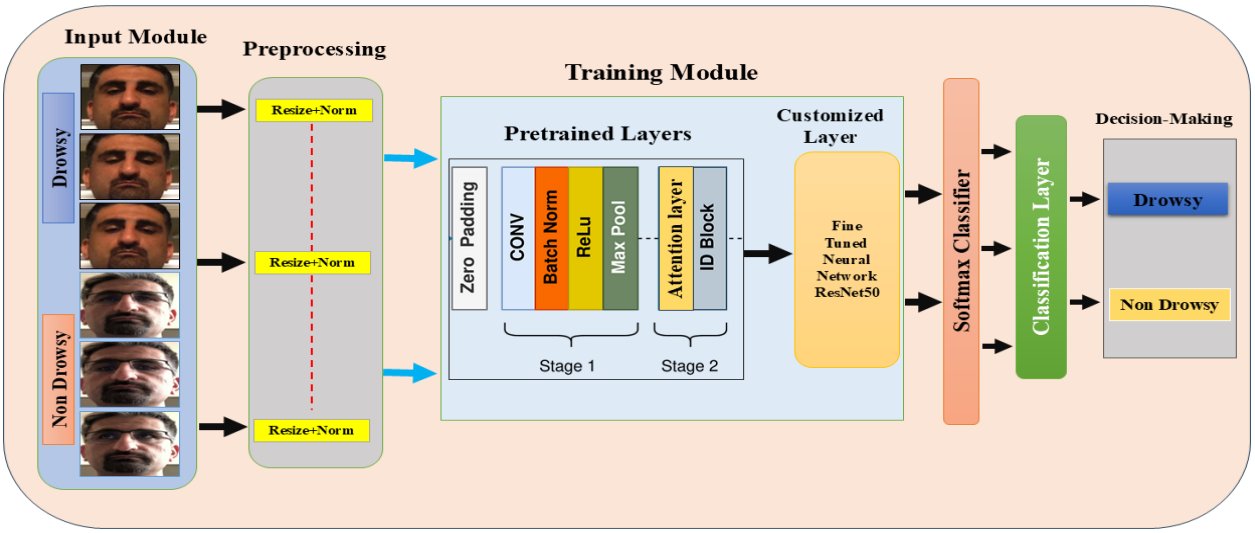


Figure 1: The main framework improves decision-making ability by combining artificial intelligence, logic, and information aggregation. For smooth data handling and training, it includes an input module, pre-processing, softmax classifier, and decision making Layer. For dynamic and intelligent applications, a strong training module and decision-making component guarantee precise and effective classification

pre-trained weights to our particular job using the Driver Drowsiness Dataset (DDD)[26]. This enables us to leverage the learnt features from big datasets and minimize training time.

Furthermore, we create a dual-input method to handle the difficulty of merging physiological and visual data:

The ResNet50 model processes the visual data and learns facial expressions and features that indicate tiredness. A completely connected network (FCN) receives the physiological data, including heart rate and blink rate, and logically aggregates it[4]. The final decision layer then combines the outputs from both models and determines whether the driver is alert or sleepy.

3.3 Training the model

This section describes the training procedure for the ResNet50 model, including data augmentation techniques, optimization algorithms, training and validation datasets, and strategies for overfitting prevention.

3.3.1 Data augmentation

To enhance model generalization and prevent overfitting, we applied a set of data augmentation techniques to the input images. These transformations help the model learn invariant and robust features by simulating real-world variations. The applied augmentations include:

- **Random Horizontal Flipping** Each image has a 50% chance of being flipped to improve spatial invariance.
- **Random Rotation** Images are rotated within a range of ± 15 degrees to simulate different viewing angles.
- **Brightness and Contrast Adjustment** Random changes in brightness and contrast ($\pm 20\%$) to account for varying lighting conditions.
- **Gaussian Noise Addition** Introduced to improve robustness against noise in real-world scenarios.

3.3.2 Optimization and loss function

For training the model, we employed the Adam optimizer, a widely used variant of stochastic gradient descent (SGD) that adapts learning rates based on first-order and second-order moment estimates. Adam is particularly effective for non-stationary objectives and sparse gradients, making it suitable for deep learning tasks like sleepiness detection. Additionally, we compared its performance with standard SGD to ensure optimal model convergence

Since sleepiness detection is a binary classification problem, binary cross-entropy was chosen as the loss function due to its effectiveness in handling probabilistic outputs. The loss function is defined as

$$L = -\frac{1}{N}\sum_{i=1}^{N} y_{true}\log(y_{pred}) + (1-y_{true})\log(1-y_{pred}) \tag{2}$$

where:

- N is the number of training samples,
- y_{true} is the true label,
- y_{pred} is the predicted probability.

3.3.3 Regularization and overfitting prevention

To prevent overfitting, we incorporated the following regularization techniques

DropoutA dropout rate of 0.5 was applied to the fully connected layers, randomly deactivating neurons during training to promote generalization

L2 Regularization Also known as weight decay, L2 regularization was applied to penalize large weights, encouraging the model to favor simpler solutions and reducing sensitivity to noise [27]

3.3.4 Hyperparameter tuning

We utilized an NVIDIA RTX 3060 GPU with 12 GB of VRAM to train and evaluate our model, ensuring efficient processing of high-dimensional image and physiological data. The model was optimized using the Adam optimizer with a learning rate of 0.001 and a batch size of 64. Training was conducted for 100 epochs with early stopping to prevent overfitting

These measurements are crucial for comprehending the trade-offs between reducing false alarms (precision) and accurately recognizing sleepy drivers (recall). The model strikes a balance between the two metrics when the F1-score is high.

3.3.5 Attention mechanisms for better decision-making

In our model, we integrate AI predictions with physiological features using an attention mechanism that enhances decision-making by considering additional context provided by physiological signals, such as heart rate variability. While the ResNet50 model provides initial predictions, these predictions are refined through the attention mechanism, which weighs the significance of physiological signals in determining the final decision. The goal is to improve the reliability of the system, especially in cases where the model's confidence is low

For example, even if the AI model's confidence in its prediction is low, the attention-based system can override its output if physiological data, such as heart rate variability, indicates significant levels of stress or exhaustion. Heart rate variability (HRV) is a physiological measure that reflects the variation in time intervals between heartbeats. HRV can be computed using the standard deviation of the RR intervals (the time between successive R-wave peaks in an ECG signal), with higher variability typically indicating better cardiovascular health and lower variability suggesting stress or fatigue [28] To formalize the decision-making process, we use the following equation that combines the AI prediction with the physiological signal in an attention-based manner

$$Decision = f(AIPrediction, PhysiologicalSignal)$$

Where: - $f(\cdot)$ represents the attention mechanism that weights the importance of each input (AI prediction and physiological signal) to generate the final decision. - The physiological signal (e.g., heart rate variability) is used to adjust the prediction based on its relevance to the context (e.g., stress or exhaustion)

This approach ensures that the model makes a more reliable and accurate decision by taking into account both AI predictions and important physiological features

4 Results

The experiments that was carried out to assess the artificial intelligence model's ability to identify driver sleepiness using the Driver sleepiness Dataset (DDD) are presented in this part. In order to make reliable decisions, the experiments aim to evaluate how well information aggregation from physiological signals (such heart rate variability) and picture data (collected through face features) can be combined [29]. Additionally assessed is the incorporation of a attention mechanism to improve the decision-making process.

4.1 Dataset

The Driver Drowsiness Dataset (DDD) is a database of more than 41,790 photos taken under various circumstances showing drivers while they are alert and sleepy. This dataset is crucial for the training and assessment of machine learning models that use eye movements and facial expression analysis to identify driver drowsiness. Real-time driver monitoring systems that warn of possible drowsiness in drivers and aid in preventing collisions can then be developed using these models[30].

4.2 Experimental setup

The ResNet50 model and the Driver Drowsiness Dataset (DDD) were used in a number of studies to evaluate the model's performance. To guarantee a balanced distribution of alert and sleepy instances, the dataset was divided into training (80%) and testing (20%) sets [31] [32]. Both image and physiological feature data were used to train the model, and the suggested attention mechanism was used to aggregate the data modalities.

The impact of information aggregation on the overall classification accuracy was investigated through studies using various combinations of physiological and visual data.

4.3 Results of AI model without attention-base integration

The driver's facial features were used as the only image data used to train the ResNet50 model in the first set of tests; physiological signals were not included. The following table provides an overview of these experiments'

findings:

Table 1: Performance metrics for the model

Metric	Value (%)
Accuracy	85.4
Precision	86.1
Recall	84.3
F1-Score	85.2

Even while the ResNet50 model demonstrated encouraging results when using only picture data, there were still several situations in which the model had trouble correctly identifying drowsiness, especially when the driver's facial expressions were unclear or subtle[11].

4.4 Results of AI model with physiological data integration

Along with photographic data, the physiological data (heart rate, blink rate, and eye movement speed) was incorporated into the model in the subsequent tests. This enabled the model to execute information aggregation, in which a final classification decision was made using both forms of input. The outputs from the physiological characteristics and the ResNet50 model were combined using the attention mechanism [33]. The experiment's findings are compiled in the table 2

Table 2: Performance metrics for the model, showcasing its accuracy, precision, recall, F1 score, and overall efficiency

Metric	Value (%)
Accuracy	90.2
Precision	91.0
Recall	89.1
F1-Score	90.0

These results show that the model's accuracy in identifying driver tiredness is much increased by the information aggregation of physiological signals and picture data[36]. More accurate predictions were made possible by the attention-base combination of these two data sources, particularly when one data source was insufficient to produce an appropriate categorization[11].

4.5 Results of AI model with attention mechanism for enhanced decision-making

Another set of experiments was conducted to evaluate how well the attention mechanism improved the decision-making process. In this configuration, the ResNet50 model used both physiological and image data to assess whether the driver was alert or sleepy. The results were then processed through a decision rule logic framework [37] [38]. This decision rule took into account physiological indicators of weariness, such as an elevated heart rate or an irregular blink rate, along with the AI predictions' confidence level. This approach, which combined artificial intelligence predictions with attention-based decision-making, outperformed the earlier setups [21]. By integrating physiological data with AI outputs, the attention mechanism enhanced the predictions, especially in more complex situations [4].

The decision rule was designed to incorporate both the AI predictions and the physiological signals, ensuring a more accurate final decision.

The results of this experiment are shown in Table IV.

4.6 Comparison of different models

The list of results below provides a summary and comparison of the outcomes of the several experimental configurations[1]. This comparison shows how the attention mechanism and information aggregation affect the model's classification performance[3][39][40].The results of the different technique they we explore through experiment are shown in 5 table:

4.7 Ablation study

To determine how every element information aggregation, logic-based reasoning, and the artificial intelligence model affects system performance, an ablation research was carried out[41][42]. The results showed that combining logic and multimodal information aggregation greatly increased accuracy, reaching 93.5%. Performance decreased when the physiological data or attention mechanism were removed, underscoring the significance of integrating these components for reliable classification[43][44].comparison Table 3 and fig.2 showcasing the performance of our proposed framework against other notable works in driver drowsiness detection, highlighting key metrics and methodologies[45][46]:

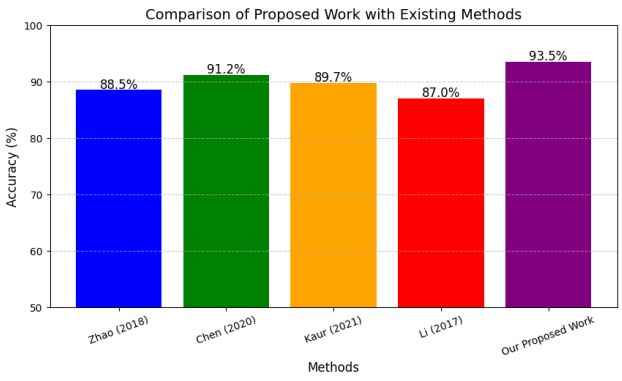


Figure 2: Driver drowsiness detection accuracy: proposed method vs. existing approaches

Table 3: Comparison of Proposed Work with Existing Methods

Method	Key Features	Accuracy (%)	Use of Logic	Information Aggregation
Zhao [34]	Convolutional Neural Networks	88.5	No	No
Chen [35]	EEG and Eye Tracking Fusion	91.2	No	Yes
Kaur [12]	CNN + Support Vector Machines	89.7	No	Partial
Li [7]	only resNet50	87.0	No	No
Our Proposed Work	ResNet50 + Attention mechanism	**93.5**	**Yes**	**Yes**

Table 4: Performance metrics for the model

Metric	Value (%)
Accuracy	93.5
Precision	94.2
Recall	92.7
F1-Score	93.4

4.8 Qualitative results

Our proposed system's qualitative results show that it can use artificial intelligence, information aggregation, and a attention mechanism to accurately detect driver tiredness[21]. With a high accuracy of 93.5%, the technology demonstrates its usefulness in practical applications. Here, we examine the model's performance using information from a representative classification image and a confusion matrix.

4.8.1 Confusion matrix analysis

The confusion matrix in Fig. 3 provides a detailed analysis of the model's classification performance for the "Drowsy" and "Non-Drowsy" states. The model successfully identified 2,189 drowsy instances and 1,990 non-drowsy instances, demonstrating high accuracy. Notably, there was only one false negative (a drowsy state misclassified as non-drowsy) and no false positives, indicating the model's strong reliability in detecting drowsiness. This precise classification highlights the effectiveness of the proposed approach in minimizing misclassification errors, ensuring robust performance in real-world applications. Additionally, the integration of logical reasoning techniques [32] and AI-driven methodologies [39] further enhances the model's decision-making capabilities, contributing to improved detection accuracy

4.8.2 Classification representation

The classification image that follows provides a visual representation of the system's decision-making process. It demonstrates how visual elements like eye closure and facial alignment are extracted from driver photos by artificial intelligence while also integrating physiological information like blink rate and heart rate variability[47]. By integrating different data streams and clearing out ambiguities in difficult situations, the attention mechanism improves classification accuracy that you can see the results in fig 4.

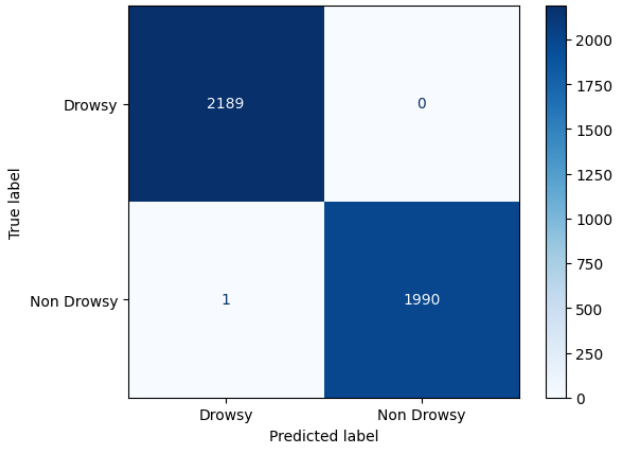


Figure 3: The confusion matrix highlights the model's performance: 2189 true positive (drowsy) predictions, 1990 true negative (non-drowsy) predictions, 1 false positive, and no false negatives

Artificial Intelligence Key facial traits that indicate driver states are correctly identified by the ResNet50 model.
Information Aggregation In situations where picture data alone is inadequate, physiological data offer extra context.
Logic Framework In situations like low light levels or occlusions (like sunglasses), the decision rules provide high dependability by resolving ambiguities.

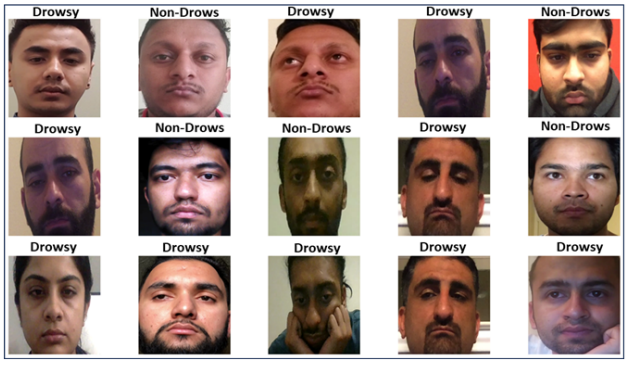


Figure 4: Visual examples of 'drowsy' and 'non-drowsy' faces, showcasing the model's classification accuracy

4.9 Experimental results and discussion

The experimental results demonstrate that integrating an attention mechanism with physiological signals and ResNet-

Table 5: Comparison of metrics for different model configurations

Metric	ResNet50 (Image Only)	ResNet50 (Image + Physiological)	ResNet50 + attention mechanism
Accuracy	85.4	90.2	93.5
Precision	86.1	91.0	94.2
Recall	84.3	89.1	92.7
F1-Score	85.2	90.0	93.4

50 significantly enhances driver drowsiness detection. The baseline ResNet-50 model, trained only on image data, achieved an accuracy of 85.4% but struggled with cases where facial cues were subtle. Incorporating physiological signals such as heart rate, blink rate, and eye movement speed improved accuracy to 90.2%, highlighting the benefits of multimodal fusion. The best performance, with an accuracy of 93.5%, precision of 94.2%, recall of 92.7%, and F1-score of 93.4%, was achieved when an attention mechanism was used for decision-making. This improvement underscores the mechanism's ability to refine feature selection and enhance robustness

Compared to state-of-the-art methods, our model outperforms CNN-based approaches, such as Zhao et al. (88.5%) and Kaur et al. (89.7%), and achieves comparable accuracy to EEG-based systems like Chen et al. (91.2%). However, unlike EEG-based methods, which require intrusive sensors, our approach is non-intrusive and scalable, making it more practical for real-world applications. The attention mechanism plays a critical role by dynamically focusing on relevant visual and physiological cues, preventing misclassifications caused by variations in lighting conditions, facial occlusions, or transient physiological fluctuations

These findings highlight the effectiveness of AI-driven information aggregation in enhancing decision-making for driver monitoring systems. The proposed framework provides a scalable and efficient solution for real-time drowsiness detection. Future work could explore multi-sensor integration, such as vehicle dynamics data, to further improve accuracy. Additionally, expanding the dataset to include diverse driving conditions and enhancing model interpretability would contribute to the broader adoption of AI-based driver safety systems

5 Conclusion

The current research presented a methodology for detecting driver drowsiness that combines information aggregation, artificial intelligence, and logic-based decision-making. By combining physiological data like heart rate and blink rate with visual features from the ResNet50 model, the method improved reliability through information aggregation.

Performance was enhanced with the addition of attention mechanism, attaining 93.5% accuracy, especially in difficult situations. the findings showed that integrating information aggregation, artificial intelligence, and logic produces a solid solution for practical safety-critical applications, laying the groundwork for intelligent systems of the future.

6 Funding

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Optimizing Swarm Intelligence: A Comprehensive Analysis of Mutation-Based Enhancements

Muchamad Kurniawan*[1], Gusti E. Yuliastuti[1], Siti Agustini[2], Maftahatul Hakimah[1], and Wahyu Widyanto[1].
[1] Institut Teknologi Adhi Tama Surabaya/ Department of Informatics, Surabaya, Indonesia
[2] Institut Teknologi Sepuluh Nopember/ Electrical Engineering, Surabaya, Indonesia
E-mail: muchamad.kurniawan@itats.ac.id, gustieky@itats.ac.id, 7022211005@student.its.ac.id, hakimah.mafta@itats.ac.id, wahyuuwy01@gmail.com
*Corresponding author

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Swarm Intelligence (SI) represents an optimization approach inspired by the collective behavior observed in swarms during the search for food. Well-established SI methods, such as Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC), are complemented by newer methodologies like Cat Swarm Optimization (CSO) and Grasshopper Optimization Algorithm (GOA). Typically, exploration techniques in SI are more effective than exploitation techniques. To enhance exploration capabilities, this research employs a modification technique based on mutation, chosen for its strong exploratory attributes and low complexity.

This study introduces 16 modifications by combining four frameworks with four operators. Each modification is paired with the fundamental methods for comprehensive testing. The experimental phase encompasses five benchmark functions of varying dimensions, resulting in 8,000 experiments. Three analytical assessments were conducted based on these results.

The initial analysis reveals that the mutation modification has the most substantial impact on the basic ACO method. The second analysis indicates that mutation modification significantly influences the objective function in scenarios with large dimensions. The concluding analysis highlights the paramount influence of the modification incorporating the random parameter mutation framework, whereas the mutation operator modification shows comparatively less significant results.

A detailed impact assessment shows that Modification 2B achieved the highest number of positive results, succeeding in 69 out of 100 tests, while 2D modifications yielded the smallest sum and average values. The influence of different frameworks and operators was further analyzed, revealing that frameworks have a more pronounced impact on performance than operators. Framework number 2, in particular, demonstrated the most significant effect on improving average impact values.

Povzetek: Analiziran je vpliv mutacijskih izboljšav na algoritme inteligence rojev (SI), kot so ACO, PSO, ABC, CSO in GOA. Predstavlja 16 modifikacij z združevanjem štirih okvirov in štirih operatorjev mutacije s ciljem izboljšanja raziskovalnih sposobnosti algoritmov. Rezultati kažejo, da imajo okviri mutacije večji vpliv na učinkovitost kot operatorji, pri čemer modifikacija z naključnim parametrom mutacije dosega najboljše rezultate.

1 Introduction

Optimization is a pivotal method used to achieve the most optimal results from an objective function. Optimization methods are generally classified into classic and modern approaches, with frameworks categorized as either metaheuristics or heuristics. Metaheuristic optimization algorithms can be further distinguished based on behavioral similarity or artificial sources of intelligence.

Early metaheuristic optimization algorithms predominantly focused on evolution and swarm intelligence, with a particular emphasis on swarm-based algorithms [1]. Evolution-based algorithms, such as Genetic Algorithm (GA) and Differential Evolution (DE), use selection, crossover, and mutation operators. Swarm intelligence algorithms, like Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Cat Swarm Optimization (CSO), and Grasshopper Optimization Algorithm (GOA), rely on internal swarm interactions to facilitate various search solutions. On the other hand, swarm intelligence algorithms are typified by interactions within the internal swarm. These interactions serve diverse purposes, such as facilitating various search solutions or inducing alterations in particle values. Notable examples of swarm intelligence algorithms comprise Ant Colony Optimization (ACO), Artificial Bee Colony (ABC), Particle Swarm Improvements in exploration using the mutation operator have been applied to enhance the standard Particle Swarm Optimization (PSO) [8], [9]. The Hybrid PSO with Mutation Operator (HPSOM) method was developed specifically for implementation as a clustering algorithm, demonstrating superior results compared to two other optimization algorithms across six measurements and datasets [4].

Wang et al. proposed PSO Mutation (MPSO) to address multi-objective function problems, specifically with thermoelectric generator (TEG) datasets [10]. In this study, the mutation process is controlled by a parameter with a random value. If the random value exceeds the parameter value, one individual undergoes mutation; otherwise, a position change is made, akin to standard PSO.

Exploration and exploitation are two key techniques within optimization algorithms. Exploration refers to the algorithm's ability to search the entire space for the optimal solution, while exploitation involves refining solutions to converge towards the optimal outcome. Swarm intelligence methods typically excel at exploitation but often struggle with exploration, leading to premature convergence and suboptimal solutions.

To enhance the exploration capabilities of PSO, Jana et al. introduced the repository and mutation technique to create RMPSO. The fitness values and convergence rates of RMPSO were compared with seven previously modified PSO studies [11]. Optimization (PSO), Cat Swarm Optimization (CSO), and Grasshopper Optimization Algorithm (GOA) [2]. It is noteworthy that the landscape of metaheuristic optimization is dynamic, continually witnessing the assimilation of novel algorithms and techniques.

Exploration and exploitation represent two pivotal techniques within optimization algorithms. Exploration pertains to the algorithm's efficacy in locating the optimal solution across the entire search space. Conversely, exploitation involves the capacity of individuals to update their values with the goal of converging towards the optimal solution. Generally, specific operators or parameters govern these two techniques. A higher exploitation value accelerates the algorithm's convergence to a solution, but the obtained solution is susceptible to local optima or spurious solutions. Swarm intelligence methods inherently possess heightened exploitation capabilities relative to exploration. Notably, contemporary studies have incorporated the mutation operator to enhance exploratory capabilities.

To enhance the efficacy of swarm intelligence algorithms, the incorporation of a mutation operator has been proposed as a viable solution [3] [4] [5]. The introduction of a mutation operator serves to augment exploratory capabilities, thereby preventing rapid convergence of the algorithm [6]. An additional advantage associated with the integration of the mutation operator lies in its computational efficiency compared to adjustments involving crossbreeding, modifications to alternative optimization algorithms, or alterations requiring multiple populations [7]. Various studies investigating the incorporation or modification of swarm-based algorithms with mutation operators have consistently demonstrated performance improvements.

Cat Swarm Optimization (CSO), initially proposed by Chu et al. in 2006, is a swarm-based optimization algorithm that has been employed in diverse case studies [11], [12]. While bearing resemblance to PSO, the CSO algorithm features a distinct exploration and exploitation mechanism involving two types of individuals, namely seekers and tracers. A 2018 study reported that the incorporation of a mutation operator into CSO enhances optimal global search capabilities, particularly in high dimensions [14].

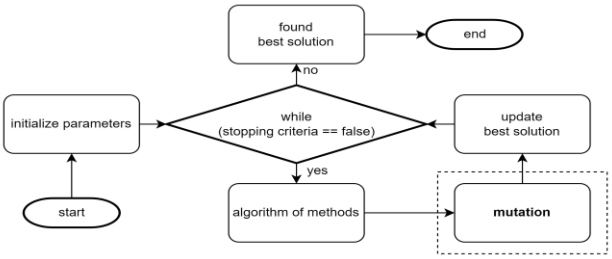


Figure 1: Hybrid framework of swarm-based optimization and mutation processes

The swarm intelligence algorithm by adopting grasshoppers in search of food was first reported by Saremi *et al*. 2017 with the name grasshopper optimization algorithm (GOA). The results of a paper survey on GOA from 2017 to 2020 stated that there were more than 200 implementation or development studies [14]. The limitation of this algorithm is that it is stuck in local optimal and convergent time [16] to be used in various cases. A development of GOA with the addition of the Caucy mutation was reported in 2021 [17]. Research conducted by Ghaleb *et al*. in 2021 using six different mutation operators implemented in GOA, the results of this study were not a significant increase when compared to the standard GOA [18].

Studies of hybrid mutation and ACO discuss the implementation of a random injection operator on ACO by looking at the diversity value of the swarm [18]. Two-point standard mutation and refined mutation are operators used in research [20], and partial ACO mutation is the algorithm's name with the GA standard operator implemented in ACO partially [21]. Cauchy mutation and ABC algorithm can improve standard ABC performance [22]. The uniform mutation is used for searching on the ABC algorithm [23]. These research show that hybrid mutation can improve performance. However, the level of randomness of the mutation technique is still low, so the resulting solution is pre-mature convergence.

To address this limitation, recent studies have incorporated mutation operators into swarm intelligence algorithms to enhance their exploratory capabilities. Mutation operators introduce random variations, preventing rapid convergence and improving the overall performance of the algorithms.

This research aims to improve the exploration capabilities of swarm intelligence algorithms by introducing a new mutation technique using novel operators and frameworks. We propose 16 different combinations of four frameworks and four operators, applied to PSO, GOA, BCO, ACO, and ABC algorithms. The goal is to achieve a more robust level of exploration, leading to more optimal solutions across various swarm-based optimization algorithms. Our contributions include demonstrating the robustness of these mutation methods and their effectiveness in enhancing the performance of swarm intelligence algorithms.

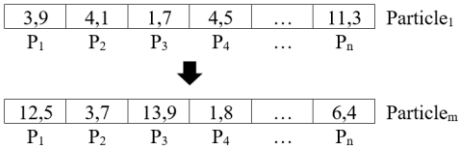


Figure 2: Full injection gaussian random mutation illustration

2 Method

Within this section, we introduce novel mutation techniques. The focus of this research is to categorize mutation into two components: operator and framework. The operator will be represented by an alphabetic code, while the framework will be denoted by a numeric code, simplifying future references. An operator refers to a method employed to modify the value of a particle. In total, there are four distinct types of operators.: (A) full injection gaussian random mutation [24], (B) n-point gaussian random injection mutation, (C) arithmetic random operator mutation, and (D) even odd random injection mutation. Framework mutation is the workflow of the mutation technique. There are four mutation frameworks used: (1) random picker particle mutation, (2) random parameter mutation, (3) sorting mutation, and (4) dynamic sorting mutation. Operators and frameworks cross combined, so there are sixteen mutation techniques: {1A,1B, …,3D,4D}. We assume that the mutation rate value, mr, is 0.3 and there are n particles.

2.1 Hybrid swarm-based and mutation technique

In general, the procedure for initializing a swarm-based algorithm is parameter initialization, searching for each particle, determining the $Gbest$, and updating each particle. This procedure will be repeated until the stopping criteria are met. The main methodology of this research is to modify optimization methods with a mutation process, so a hybrid is needed that can be implemented in all optimization methods. The algorithm used in this study (Figure. 1) is to add mutations after the algorithm process of the optimization method and then update the value for the best solution value or *Gbest* in swarm-based.

2.2 Full injection gaussian random mutation operator

This operator is a mutation operator by utilizing the Gaussian distribution to generate random numbers. The mean and standard deviation values are obtained from all particle values in each dimension. The resulting random number will be used to update the new particle with several dimensions of the objective function as shown in Figure. 2. For example, there are 5 dimensions in an objective function. Each particle that has a mutation will generate a random number of 5 dimensions.

2.3 N-point gaussian random mutation operator

In the n-point gaussian random mutation operator, the randomization process is not carried out at all positions in the particle. The first step is to determine the n number of

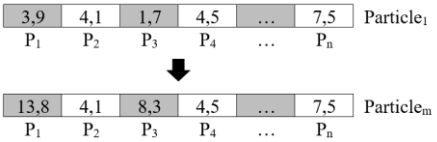


Figure 6: Even Odd Random Injection Mutation Illustration

particle positions carried out to mutation process. The second step is generating other n random value. The resulting random values will replace the particle values at these positions. So that the mutation results are obtained which experience slight changes, because not all the particles are mutated. As an illustration, the value of n is determined to be 3, then there will be 3 positions that are mutated. We need to generate 3 random values as shown in Figure. 3 and then carry out the mutation process at 3 predetermined points. The mutation process is carried out by changing the values of the 3 positions with the values generated by random value generation as shown in Figure. 4.

2.4 Arithmetic random mutation operator

The mutation process in arithmetic random mutation is carried out by involving several arithmetic operators including addition operators, subtraction operators, and multiplication operators. The multiplication operator is used for two conditions, namely the multiplication of positive values and the multiplication of negative values. The first step is to generate a random value (r_1) round value between 1 and 4. The first random value is used to determine the next selected operator process. Then the process continues to generate a second random value (r_2) with decimals. The second random value is used as the value on which the selected operator operates. If the value 1 appears, then the operator used is addition. If value 2 appears, then the operator used is subtraction. If the value 3 appears, then the operator used is the multiplication of positive values. If the value 4 appears, then the operator used is negative multiplication. The simulation of this operator can be seen in Figure. 5, when the value of $r_1 = 3$ or selected operator is multiplication, and the value of $r_2 = 3.2$ as the coefficient value, the updated particle value is obtained from the addition of the particle value with the coefficient value.

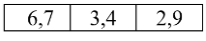


Figure 3: N random generated values

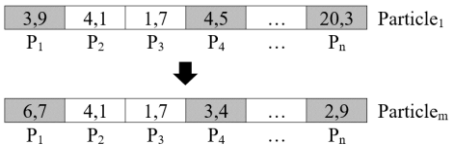


Figure 4: N-Point gaussian random mutation illustration

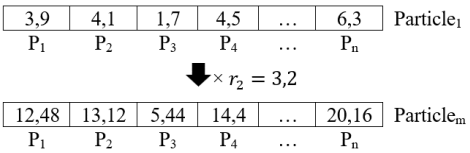


Figure 5: Arithmetic random operator mutation illustration

2.5 Even odd random injection mutation operator

The even odd random injection mutation determines the mutation process based on a binary random value as shown in Fig. 6. If the binary value is 0, then the mutation operator randomizes the value at an even position. Meanwhile, if the value 1 appears, then the mutation operator randomizes the value at the odd gene position [6]. Randomizing the values at these positions is done randomly as shown in Fig. 6. The key distinction of the B, C, and D mutation operators lies in their partial modification of vector values, specifically targeting odd or even indices. These operators involve sampling random values and assigning them to specific dimensions within the decision vector. The range of each dimension within the vector is determined by the minimum and maximum values specified in the range dimension of each objective function.

2.6 Random picker mutation framework

The random picker mutation framework begins with computing the $nMut$ value by multiplying $nParticles$ and mr. The variable $nMut$ is used to determine the number of particles that carried out to mutation process. The particles that carried out to mutation process are determined randomly. The detailed this framework can be seen in Algorithm 1.

Algorithm 1: Random Picker Mutation Framework

```
// mr is mutation rate
// particles is all particle in entire swarm
// nParticles is size swarm
nMut ← floor (nParticles ∗ mr)
for i ← 1 to nMut :
    mutIndex ← random index (particles) ;
    newParticle ← mutation operator (particles[mutIndex]);
    newFitness ← objective function (newParticle) ;
    particles [mutIndex] ← newParticle ;
    fitness [mutIndex] ← newFitness ;
end for
```

2.7 Random parameter mutation framework

The random parameter mutation framework focuses on determining which particles will undergo mutation. We assume that there are n particles. The random values, $rand_i$, where $i = 1, 2, 3, \ldots, n$, are generated and assigned each value into each particle. Each random value, $rand_i$, will be compared to mutation rate, mr. If the random value, $rand_i$ less than mutation rate, mr so the i-th particle will be carried out the mutation process. The new particle and fitness values resulting from the mutation will replace the previous values. The entire steps of algorithms can be seen in Algorithm 2.

Algorithm 2: Framework Random Parameter Mutation

```
// mr is mutation rate
// particles is all particle in entire swarm
// nParticles is size swarm
for i ← 1 to nParticles :
    if rand < mr :
        newParticle ← mutation operator (particles [i]) ;
        newFitness ← objective function (newParticle) ;
        particles [i] ← newParticle ;
        fitness [i] ← newFitness ;
    end if
end for
```

2.8 Sorting mutation framework

The Sorting Mutation Framework (Algorithm 3) works the mutation process by sorting descending particles based on their fitness values. Particles with the worst fitness value will be subject to mutation. The $nMut$ variable controls the number of the worst particle mutations carried $outMut$ variable, which is obtained from the total number of $nParticles$ multiplied by the mutation parameter mr. The mutated particles will replace the old particles.

Algorithm 3: Framework Sorting Mutation

```
// mr is mutation rate
// particles is all particle in entire swarm
// nParticles is size swarm
// fitness is return value from objective function
nMut ← floor (nParticles ∗ mr) ;
worst ← sorting desc index by (fitness) ;
for i ← 1 to nMut :
    newParticle ← mutation operator (particles[worst[i]) ;
    newFitness ← objective function (newParticle) ;
    particles [worst[i]] ← newParticle ;
    fitness [worst[i]] ← newFitness ;
```

end for

2.9 Dynamic sorting mutation framework

The basis of this framework is a sorting mutation framework with dynamic mutation arrangements. The difference is that in this framework, parameters adjust the number of dynamically mutated particles. Setting the number of mutation particles will continue to increase as the number of iterations increases. In Algorithm 4, there is a dynamic $variableMut$, the control parameter for dynamic mutations.

Algorithm 4: Framework Dynamic Sorting Mutation

```
// mr is mutation rate
// particles is all particle in entire swarm
// nPop is size swarm
// fitness is return value from objective function
// maxIter is maximum iteration
dinamicMut ← ceil (( mr/maxIter) * iter) ;
nMut ← floor (nParticles * dinamicMut) ;
worst ← sorting desc index by (fitness) ;
for i ← 1 to nMut :
    newParticle ← mutation operator (particles[worst[i]) ;
    newFitness ← objective function (newParticle) ;
    particles [worst[i]] ← newParticle ;
    fitness [worst[i]] ← newFitness ;
end for
```

2.10 Objective function

The objective function used in this study is divided into two groups. The first group is a function that has a single optimal result or is often called unimodal. The second group is a multimodal function. In the unimodal group the objective functions used are the De Jong, and Rosenbrock functions and the other group functions are Rastrigin, Griewank, and Ackley. The equation used for the De Jong function can be seen in Eq. (1), the Rosenbrock function uses Eq. (2), the Rastrigin, Griwank, Ackley functions use Eq. (3)-(5).

$$f(x) = \sum_{i=1}^{n} x_i^2 \quad (1)$$

$$f(x) = \sum_{i=1}^{n-1}[100(x_{i+1} - x_i^2)^2 + (1 + x_i)^2] \quad (2)$$

$$f(x) = 10n + \sum_{i=1}^{n}[x_i^2 - 10\cos(2\pi x_i)] \quad (3)$$

$$f(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \quad (4)$$

$$f(x) = -a \cdot \exp\left(-b \cdot \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(c.x_i)\right) + a + \exp(1) \quad (5)$$

Table 1. Setup parameters of SI

Method	Parameter
PSO	$c_1 = 1; c_2 = 2$
ACO	$alpha = 1;\ beta = 3;\ rho = 0.1$
CSO	$smp = 10;\ mr = 0.2;\ spc = True;$ $cdc = 1;\ srd = 0.01;\ c_1 = 0.5$
GOA	$c_{min} = 0.1;\ c_{max} = 1;$ $lower_{bound} = 1;\ upper_{bound} = 1.5$
ABC	$bee_{explore} = 8; num_{sourcefood} = 2;$

3 Result and discussion

In this study the optimization method or algorithm used is PSO, GOA and ACO. Mutation modification will have 16 modifications from 4 types of frameworks and 4 types of mutation operators that will be added to each method. To make it easier to read, the method given the mutation modification will be affixed with the letter 'M' which indicates modified followed by the code number which indicates the mutation. There are 6 types of benchmark functions used: Rosenbrock, De Jong,

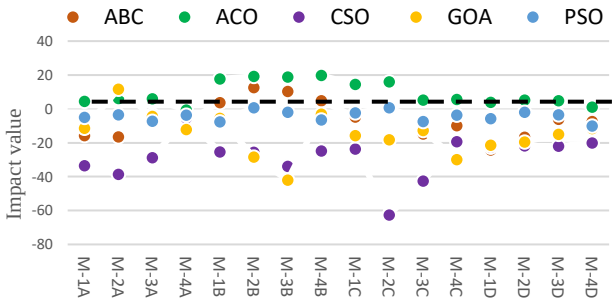


Figure 7: Accumulated total impact value.

Rastrigin, Greiwangk, and Ackley with 4 different dimensions (2, 5, 10, and 30). Because the initial initialization uses random values, to get the best results, the test is carried out ten times for one test scenario. The initialization of parameter values of SI algorithm can be seen in Table 1. These values are fixed so that can measure the effectiveness of research contributions without being influenced by other parameters.

This section will be subdivided into three analyses to ensure a comprehensive evaluation. The first analysis examines the method that exhibits the most significant impact when mutations are introduced. The subsequent analysis investigates the effects of objective function types, specifically unimodal and multimodal functions. Lastly, an analysis is conducted to determine the framework and mutation operators that exert the most substantial influence. The impact calculation is performed using Equation 6. This equation quantifies the difference between the fitness value of the baseline method, denoted as *G(x)*, and the fitness value of the modified method, denoted as *G(x)'*. The difference is divided by the fitness value of the baseline method and then multiplied by 100 to amplify the impact.

$$I = \frac{G(x) - G(x)'}{G(X)} \quad (6)$$

Table 2: Summary of the impact of mutations on basic methods

Method	Best	Worst	Average	Positive Totals
ABC	12,69	-24,15	-5,95	5
ACO	19,70	-0,68	9,24	15
CSO	-5,37	-62,56	-28,13	0
GOA	11,57	-41,96	-14,95	1

3.1 Objective function analysis

To analyze the impact of mutations on the fundamental methods, it is imperative to conduct a comprehensive comparison of mutation effects across all benchmark functions. Figure 7 illustrates the outcomes of all mutation modifications applied to the basic method, with the dotted line denoting the baseline method (having a y-axis value of zero). A positive value signifies that the modified method outperforms the basic method, while a negative value indicates inferior performance. The results of testing the basic method are presented in Figure 7, where a larger positive value denotes a more pronounced impact. Notably, among all the basic methods tested, the ACO method exhibits the most substantial impact, as evidenced by the prevalence of modified methods with values above zero. It is worth mentioning that the addition of mutation modifications exerts varying effects on the ACO method.

In addition to leveraging the difference in mean values, a paired T-Test is employed for a statistical assessment to ascertain whether the modification of the basic method yields significant positive changes. Each method modification result is paired with the method result without modification. With an alpha value of 0.05 and a t-table value of 2.9803, the T-Test results were obtained for all method results, as illustrated in Fig. 8. From these results, the modification that exhibited the most positive effect was observed in the ABC method with the M-1D modification. Among the basic methods, the one that underwent the most successful modifications was the 9th method.

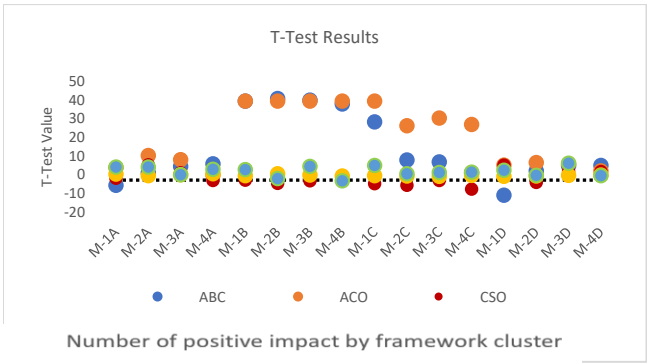
The overall summary of mutation results obtained 4 results as shown in Table 2. The first result is ACO with the M-1C modification gets the best score with a value of 19,70. The second result obtained is the value of the biggest negative impact on CSO. The third result is that only ACO has a positive value from the calculation of the average impact. The final result obtained from all experiments is that the most successful mutation modification is in the ACO method with 15 modifications (out of a total of 16 modifications).

Mutation Impact Analysis of Dimension and Function Problem

To conduct an impact analysis on the introduction of mutations to the dimensions and types of problem functions in this section, the benchmark functions and dimensions will be initially classified. The dimensions of the problem will be categorized into two types: low dimensions (2 and 5 dimensions) and high dimensions (10 and 30 dimensions). Similarly, the types of functions will be distinguished between unimodal functions (Rosenbrock and De Jong) and multimodal functions (Rastrigin, Griewank, and Ackley).

The best fitness results from 10 trials are summarized, including the best value or minimum value, worst value, average, and total, as depicted in Appendix A for unimodal functions and Appendix B for multimodal functions. Following the grouping based on the problem function, the best value results will be further categorized based on the dimensions employed.

Out of the 16 modifications applied to all basic methods and across 10 trials for each test, all basic methods exhibit the best results among the mutation modifications used. The ACO method, with its mutation modification, demonstrates the most significant positive



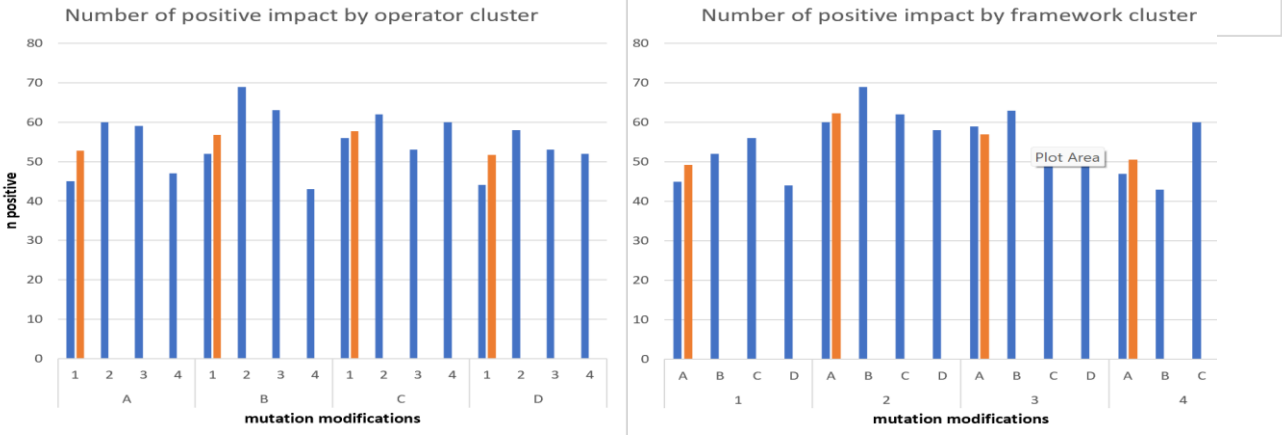


Figure 9: Number of positive impacts by cluster operator and framework mutation modification

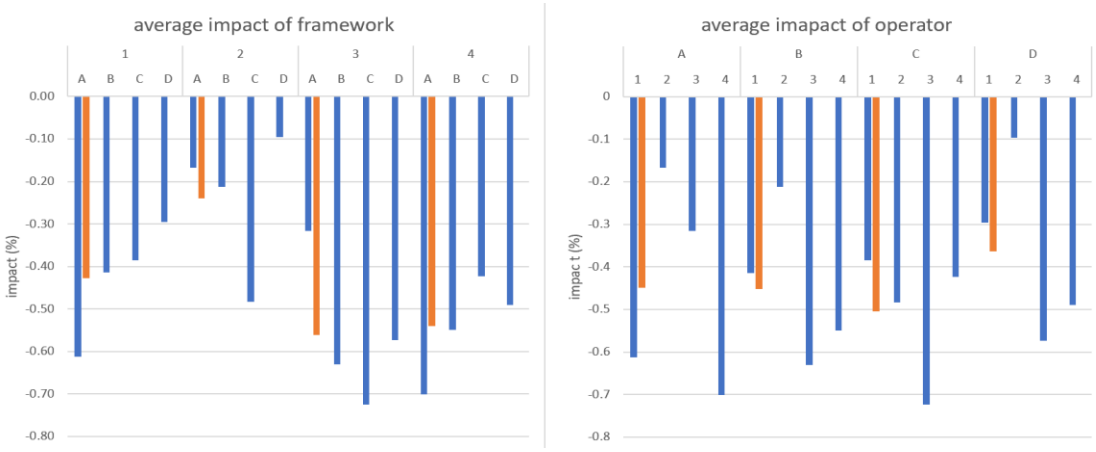


Figure 10: Number of positive impacts by cluster operator and framework mutation modification

impact, securing the best value across all groupings. The GOA method, with its mutation modification, achieves the highest result, with an impact value of 3,484 on high-dimensional unimodal functions. ACO emerges as the method with the most substantial impact, boasting an average modification value of 16 mutations with positive results across all dimensions and problem function types, totaling 0.55.

The ABC and CSO methods yield favorable results in dimensions 10 and 30 (high dimensions) for both unimodal and multimodal functions. On the other hand, PSO and GOA methods exhibit less favorable outcomes with the addition of mutations. PSO only demonstrates improved results on high dimensions with multimodal function mutations. Conversely, mutations applied to GOA show no positive effects and even exacerbate the performance of the basic GOA method, resulting in an average negative impact of mutations.

3.2 Framework and operator modification analysis

The impact of mutation modifications can be assessed through an analysis of the summary of impact values for the 5 basic methods, 4 dimensions, and 5 objective functions—essentially, the average impact value derived from 100 iterations. The summarized value encompasses the total sum, average, best, worst, and total modifications that yield positive values (n positive), as depicted in Table 7. Modification 2B stands out as the modification with the highest number of positive results, achieving success in 69 out of the 100 conducted tests. Conversely, the smallest sum and average values are produced by 2D modifications.

To analyze the influence of different frameworks and operators, the results from Table 7 are organized by framework and mutation operator. Figure 10 presents a graph illustrating the groupings of frameworks and operators based on the sum of positive results. The blue line represents the results from Table 7, while the yellow line represents the average value of the grouped operators (left picture) and frameworks (right picture).

From Figure 10, it becomes apparent that the grouping of frameworks has a more pronounced influence than that of the operators. In the grouping of operators, the average values appear consistent, whereas in the grouping of frameworks, the results exhibit variation. Modification of framework number 2 emerges with the best results, indicating that this modification has the most significant effect. Similarly, an analysis of modifications influencing the average impact value reveals that modifications with Framework 2 yield the best results based on Figure 10. The graphical pattern observed aligns with that depicted in Figure 9, which is based on operator modifications.

The study reveals that mutation modifications have a substantial positive impact on the Ant Colony Optimization (ACO) method, with 15 out of 16 modifications showing improved results. Notably, the ACO with the M-1C modification achieved the highest score of 19.70. Additionally, the Artificial Bee Colony (ABC) method with the M-1D modification exhibited significant positive effects. Among the tested frameworks, Framework number 2 emerged as the most effective, yielding the best results across various dimensions and objective functions. In high-dimensional unimodal functions, the Grasshopper Optimization Algorithm (GOA) with its mutation modification achieved the highest result. Both ABC and Cat Swarm Optimization (CSO) methods performed well in high dimensions (10 and 30) for both unimodal and multimodal functions, while the Particle Swarm Optimization (PSO) method showed improvement only in high dimensions with multimodal functions. Conversely, mutations generally worsened the performance of GOA, resulting in an average negative impact. The analysis also indicates that the grouping of frameworks has a more pronounced influence on performance than the grouping of operators, with Modification 2B standing out for its high number of positive results in 69 out of 100 tests. These findings highlight the enhanced optimization performance achieved through specific mutation modifications, emphasizing the importance of selecting appropriate frameworks and mutation techniques. The results provide valuable insights for optimizing swarm intelligence algorithms, suggesting that ACO and ABC methods are particularly suitable for problems requiring enhanced exploration, while GOA may require further refinement

for targeted applications in high-dimensional unimodal functions.

4 Conclusion

Based on the results obtained from all conducted trials in this study, it is deduced that mutation modification exerts the most substantial impact on optimization methods characterized by low complexity. Among these, the ACO, ABC, and PSO methods exhibit superior values compared to CSO and GOA. The application of T-Test analysis reveals that the ABC method demonstrates the most favorable effect in response to mutations.

A secondary conclusion drawn is that mutation modification exerts the most notable influence on multimodal problem functions and those with high dimensions. This is substantiated by the observation that mutation modification impedes the optimization methods from converging rapidly, thereby leading to more optimal results. In summary, this study affirms that the mutation modification yielding the most significant impact is the 2nd framework modification (Algorithm 2), also known as Random Parameter Mutation.

5 Future work

Expanding upon the insights gained from this study, several promising avenues for future research in optimizing swarm intelligence algorithms emerge. A pivotal direction involves advancing mutation techniques to fine-tune their efficacy within swarm intelligence frameworks. This could entail exploring adaptive mutation strategies that dynamically adjust mutation rates based on algorithmic performance feedback or hybrid approaches that integrate multiple mutation operators tailored to specific problem characteristics. Such endeavors aim to deepen the algorithms' capacity for efficient exploration and exploitation in complex optimization landscapes, thereby enhancing their robustness and adaptability.

Another critical area for exploration lies in extending the study to encompass multi-objective optimization scenarios. Investigating how mutation modifications influence the trade-offs between conflicting objectives in multi-dimensional optimization problems could pave the way for developing versatile multi-objective swarm intelligence algorithms. These algorithms would be capable of handling diverse decision-making challenges across domains such as engineering design, finance portfolio optimization, and logistics planning.

Furthermore, future research could focus on validating and refining optimized swarm intelligence algorithms through rigorous applications in real-world settings. By testing these algorithms against practical datasets and scenarios in sectors like healthcare resource allocation, industrial process optimization, and urban planning, researchers can assess their scalability, robustness, and applicability under real-world constraints and uncertainties.

Advancements could also involve exploring novel algorithmic enhancements beyond mutation. This includes investigating adaptive parameter tuning mechanisms that autonomously adjust algorithmic parameters in response to environmental changes or problem-specific dynamics. Additionally, the integration of advanced initialization techniques and meta-heuristic adaptations could further accelerate convergence rates and improve solution quality across diverse optimization tasks.

Comparative studies across mutation techniques and other state-of-the-art optimization algorithms present another promising avenue. Conducting comprehensive comparative analyses could elucidate the comparative advantages and limitations of swarm intelligence approaches relative to evolutionary strategies, gradient-based methods, and machine learning-driven optimizations in various complex optimization scenarios.

Moreover, theoretical investigations into the underlying mechanisms and mathematical foundations of mutation-based swarm intelligence optimizations could provide deeper insights into algorithmic behaviors and performance landscapes. These theoretical insights would not only enhance algorithm design principles but also contribute to advancing the theoretical foundations of meta-heuristic optimization methodologies.

Lastly, expanding the scope of benchmark functions and problem dimensions used in experimental validations would bolster the generalizability and robustness of findings. This expansion would encompass more intricate optimization landscapes and problem complexities, ensuring the thorough validation of mutation-driven enhancements in swarm intelligence algorithms across diverse and challenging optimization environments.

By pursuing these multifaceted research directions, future studies can significantly advance the field of swarm intelligence optimization. This advancement promises to elevate the practical applicability and effectiveness of swarm intelligence algorithms in tackling real-world optimization challenges across various scientific and industrial domains.

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APPENDIX A. Result of unimodal objective function

		Rosenbrock				De Jong			
		2-D	5-D	10-D	30-D	2-D	5-D	10-D	30-D
ABC	Mean	-2,88	-0,86	0,48	0,33	-1,89	-1,16	-0,65	0,39
	Sum	-46,11	-13,80	7,62	5,26	-30,19	-18,53	-10,44	6,29
	Worst	-13,43	-5,23	0,06	-0,47	-8,59	-12,56	-4,71	-0,05
	Best	0,61	0,84	0,97	0,99	0,77	1,00	0,98	1,00
ACO	Mean	0,20	**0,85**	0,53	0,55	0,68	0,37	0,60	0,52
	Sum	3,14	13,65	8,53	8,79	10,83	5,93	9,66	8,24
	Worst	-1,96	0,55	-0,08	-0,03	-0,47	-0,13	0,09	0,04
	Best	0,98	0,98	0,97	0,99	1,00	1,00	1,00	1,00
CSO	Mean	-21,22	-0,96	-0,06	-0,11	0,03	-4,06	-0,02	0,23
	Sum	-339,45	-15,32	-0,89	-1,75	0,43	-64,96	-0,26	3,66
	Worst	-52,09	-5,66	-0,87	-0,46	-2,77	-6,98	-0,64	0,05
	Best	-0,23	0,27	0,85	0,27	0,88	-0,63	0,32	0,34
GOA	Mean	0,29	-0,01	-0,26	-8,50	-1,17	-0,57	0,01	-0,01
	Sum	4,66	-0,22	-4,23	-135,93	-18,78	-9,06	0,15	-0,23
	Worst	0,00	-0,23	-0,52	-37,61	-4,42	-2,09	-0,67	-0,13
	Best	0,63	0,16	0,02	13,30	0,93	0,66	0,48	0,15
PSO	Mean	0,59	-0,89	0,03	0,10	0,09	-0,39	0,17	-0,02
	Sum	9,43	-14,24	0,41	1,66	1,49	-6,17	2,65	-0,36
	Worst	-0,14	-2,35	-0,80	-0,31	-2,19	-1,88	-0,60	-0,15
	Best	1,00	0,05	0,84	0,49	0,99	0,46	0,63	0,32

APPENDIX B. Result of multimodal objective function

		Rastrigin				Griewangk				Ackley			
		2-D	5-D	10-D	30-D	2-D	5-D	10-D	30-D	2-D	5-D	10-D	30-D
ABC	Mean	0,03	0,01	0,28	0,19	-1,26	-0,05	0,16	0,28	-0,23	0,43	0,19	0,25
	Sum	0,54	0,19	4,45	3,04	-20,08	-0,79	2,64	4,56	-3,71	6,83	3,08	3,95
	Worst	-1,09	-0,81	-0,20	-0,29	-3,61	-1,43	-0,32	-0,15	-1,39	-0,05	-0,05	-0,01
	Best	0,99	1,00	0,94	0,92	0,75	0,78	0,96	1,00	0,93	0,94	0,86	0,99
ACO	Mean	0,16	0,38	0,37	0,33	0,16	0,38	0,37	0,33	0,61	0,37	0,40	0,36
	Sum	2,57	6,06	5,84	5,31	2,57	6,06	5,84	5,31	9,68	5,93	6,39	5,76
	Worst	-2,05	-0,31	0,00	0,00	-2,05	-0,31	0,00	0,00	-0,01	-0,13	0,00	0,00
	Best	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00	1,00
CSO	Mean	-0,23	-0,37	0,11	-0,01	0,32	-0,19	0,06	0,08	-1,31	-0,48	0,03	0,01
	Sum	-3,75	-5,84	1,76	-0,12	5,10	-3,05	1,02	1,20	-20,99	-7,61	0,49	0,21
	Worst	-5,26	-1,06	-0,08	-0,10	-0,51	-1,33	-0,39	-0,15	-6,31	-1,10	-0,08	-0,02
	Best	0,88	0,50	0,44	0,13	0,96	0,55	0,38	0,33	0,61	0,65	0,13	0,06
GOA	Mean	-0,26	0,06	0,06	-0,11	-2,29	0,10	0,05	-0,10	-2,29	0,10	0,05	-0,10
	Sum	-4,19	0,93	0,93	-1,70	-36,63	1,57	0,87	-1,61	-36,63	1,57	0,87	-1,61
	Worst	-2,41	-0,32	-0,07	-0,21	-3,30	-0,33	-0,17	-0,37	-3,30	-0,33	-0,17	-0,37
	Best	0,99	0,47	0,34	0,06	-0,62	0,47	0,28	0,17	-0,62	0,47	0,28	0,17
PSO	Mean	0,25	0,21	0,16	0,06	-1,78	0,03	-0,39	-0,01	-2,31	-0,09	0,07	-0,03
	Sum	4,07	3,39	2,63	0,92	-28,52	0,53	-6,29	-0,20	-37,03	-1,50	1,06	-0,56
	Worst	-0,38	-0,04	-0,01	-0,02	-3,96	-0,47	-1,14	-0,26	-4,33	-0,32	-0,02	-0,07
	Best	0,86	0,55	0,28	0,15	-0,23	0,54	0,36	0,29	0,64	0,20	0,16	0,01

A Context-Aware Recommendation System with Effective Contextual Pre-Filtering Model

Duaa H. Hameed*, Rehab F. Hassan
Department of computer science, University of technology- Iraq, Baghdad, Iraq
E-mail: cs.21.22@grad.uotechnology.edu.iq, rehab.f.hassan@uotechnology.edu.iq
*Corresponding author

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Informational resources have significantly expanded as a result of the growth of the internet. Consequently, making personalized suggestions about different types of information, goods, and services is the best strategy to assist customers in solving the issue of information overload. As a result, recommendation systems are employed to aid clients in locating the products most appropriate to their interests. The majority of traditional recommender systems rely on a traditional model that just takes into account user-item-rating interactions without taking context into account. It has been demonstrated that context-aware recommender systems deliver improved predicted performance across a variety of areas by attempting to adapt to users' preferences across various settings. This study presents a proposed system to help the recommender system solve its difficulties in producing accurate predictions that are relevant to the user's preferences. The system is the Contextual Pre-filtering Based Collaborative Filtering (CPBCF) model, which is based on splitting items. To decrease the time and space needed for processing correlations, it depends on the recommended splitting approach utilizing the variance equation, which decreases the dataset depending on the most important attributes. In the proposed system experiments, the performance of CPBCF with and without contextual pre-filtering was enhanced by (5-7%) for the precision, (7-8%) for the recall, and (7-8%) for the f1-measuer. While the complexity time has enhanced by (3-4 sec). The effectiveness of the CPBCF model was evaluated using various numbers of neighbors. We can observe that neighborhood size does have an effect on forecast accuracy.

Povzetek: Kontekstno ozaveščeni priporočilni sistem z učinkovitim modelom kontekstnega predfiltriranja (CPBCF) izboljšuje kvaliteto priporočil z upoštevanjem kontekstnih informacij in uporabo metode razdelitve podatkov na podlagi variance.

1 Introduction

Finding what is needed among the vast amount of data in today's information-overloaded environment is difficult [1]. System designers suggested the Recommendation System (RS) as a solution for this issue [2]. By improving customers' ability to select the ideal products based on their preferences, RSs aim to improve the efficiency of E-Commerce (EC) systems [3]. Due to RS's importance in the field of EC, both the business community and people in general have shown an interest in it [4]. Recommendations are helpful in a wide range of circumstances, including recreation, online shopping, social networking, job portals, locating relevant web pages, and many more [5]. Several businesses, including Amazon.com, Netflix, Half.com, CDNOW, J.C. Penney, and Procter & Gamble, are examples of those that have successfully used commercial RSs. Additionally, these businesses reported higher client loyalty and better online and catalog sales [6].

In the past, user and item dimensions have been used as the basis for RSs, working under the assumption that a set of N things will interest M users [7]. The quality of these traditional RS suggestions has been reported to be somewhat low over time due to the uniformity of the information sources and a lack of user and item data [8]. It is usually affected by additional and varied criteria, sometimes referred to as "contextual factors," when determining how exactly an object is rated [9]. According to Dey et al., “Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves.” Contextual information may therefore be crucial in RS [10]. The Context-Aware Recommendation System (CARS) has recently offered more precise and enjoyable suggestions for customers by incorporating contextual information into the RS process. Consequently, depending on the results of the scoring system, user, item, and context information are incorporated into the settings. When incorporating contextual information into CARS, there are three difficulties to be resolved: contextual pre-filtering, contextual post-filtering, and contextual modeling [11]. Use contexts as filters in contextual pre-filtering methods to eliminate pointless rating profiles. The suggestion list may then be created by applying any standard recommendation algorithms to the remaining ratings [12]. In the post-filtering stage, it initially ignores contextual

information and then uses any standard Two Dimension (2D) RS on the entire dataset to forecast ratings. After that, each user's final list of suggestions is altered (contextualized) based on the contextual data [13]. In contextual modeling, the context information is immediately included in the suggested strategy in this recommendation technique, for example, as a step in the priority calculation process [11].

The remainder of the paper is divided into the following sections: There is a literature review in Section II. Section III explains the recommended method, which identifies the most important feature from the user's self-evaluation to produce contextualized suggestions. Section IV focuses on the experimental results of the proposed system. In Section V, the discussion is cleared. In Section VI, the conclusion is presented.

2 Literature review

Studies and research efforts indicate numerous approaches to creating customized CARS, as seen below.

In 2018, A. Bozanta and B. Kutlu suggested that in order to get around each method's limitations, a hybrid recommendation model be utilized to mix user- and item-based Collaborative Filtering (CF), Content-Based Filtering, and contextual data. Additionally, it is predicted for each user-venue conjunction under which specific circumstances the user would choose a certain venue. Additionally, each user has their own individually defined threshold values that signify their choice of a venue. In order to evaluate the results, experiments involving precision, recall, F1-measure, and user studies were employed. In both a user study and an experimental evaluation utilizing a real-world dataset, the RS outperformed the baseline system [14].

In 2019, M. Singh et al. proposed a novel approach based on splitting criteria for usage in apps for movie selection. This method creates a modified dataset that splits the original single item into two virtual items based on contextual value. The single user is then split into two virtual users based on contextual factors. Only when there is a significant difference between two virtual objects can a person or object be separated. Further, user-based CF is used to provide useful suggestions. The results show that the proposed technique is effective in light of several performance measurement criteria using the LDOSCOMODA dataset [15].

In 2019, Jesús Silva et al. might evaluate the effectiveness of collaborative systems for directing and assisting students in this decision-making process by looking at how these systems operate and how they impact the use of data that is different from the formal information that students frequently use. The research used the clustering-based Multi Dimension tensor factorization approach to develop an RS and demonstrate that the inclusion of tensors improves the suggestions' accuracy. This strategy enables the user to use contextual information to solve the sparsity issue and enhance recommendation accuracy [16].

In 2020, I. M. AL Jawarneh et al. created a hybrid algorithm that takes a contextual incorporation pre-filtering strategy and adapts and repurposes it, giving a new dimension to a DL-based neural CF method and recovering the advantages of both without their drawbacks. They also provided numerical results suggesting statistically significant margins of improvement for our method over the baselines [17].

In 2021, K. V. Rodpysh et al. introduced the innovative context-aware CSSVD recommendation method. The DPCC and IFPCC similarity criterion matrices, as well as the item's user property attribute matrices, were initially constructed in the CSSVD matrix before being used to produce the SSVD matrix for the Cold Start Problem (CSP). In the second phase, the context matrix is created utilizing the contextual data and the CWP similarity criteria. This matrix, which is based on the SSVD matrix created in the previous stage, creates a three-dimensional matrix based on tensor properties and solves the sparse data issue. They have used IMDB and STS data collection because they are evaluating the recommended approach by taking into account user characteristics, object properties, and contextual information. Experiential data demonstrate that the recommended algorithm CSSVD is equal to TF, HOSVD, BPR, and CTLSVD in terms of accuracy, recall, F1-measure, and NDCG measure. The results show how decreasing CSP and sparse data have enhanced suggestions to customers [11].

In 2021, Z. El Yebdri et al. trust statements have been used as a rich information source with context compensation in the development of a hybrid trust-based, context-aware post-filtering technique. This approach utilized the relative average difference between the context on the CF output that is trust conscious by adding explicit and implicit trust information. They used the idea of trust prior to generating predictions in order to exclude those with little trust from the confidence network. The results of the studies show that the recommended method outperforms suggestion techniques and standard RS on real-world datasets [18].

Table 1, which lists several methods used in various fields and displays the assessment criteria that authors employed to evaluate the efficiency and precision of the system.

3 Methodology

With the help of this suggested methodology, movies are recommended while taking numerous contextual factors into account. For Improve the accuracy of recommendations with contextual pre-filtering. Contextual factors have the ability to have an important impact in addition to explicit ratings in affecting user preferences. The dataset is reduced based on the contextual attribute, and a suggestion list is created using the smaller dataset.

Table 1: A comparative analysis of the CARS

Author, year	Dataset	Technique	Result
(A. Bozanta	Real-world dataset	A hybrid recommendati	Precisio n 0,282,

and B. Kutlu, 2018) [14]		on model can be utilized to mix user- and item-based collaborative filtering (CF), content-based filtering, and contextual data	Recall 0,276, F1-measure 0,279
(M. Singh et al., 2019) [15]	LDOSCOMODA dataset	Splitting criteria for usage in apps for movie selection	MAE 0,9024
J. Silva et al., 2019) [16]	Studied dataset	Clustering-based multi-dimensional tensor factorization	Recall 0,65, Precision 0,81, MAE 1,06
(, I. M. AL Jawarneh et al., 2020) [17]	Movielens 1M, DePaulMovie, and TripAdvisor datasets	Hybrid algorithm that takes a contextual incorporation pre-filtering strategy and adapts and repurposes it	MAE 2,35%, Accuracy 6.4%
(K. V. Rodpysh et al., 2021) [11]	STS and IMDB datasets	Context-aware CSSVD recommendation	RMSE 1,007, Precision 0,361, Recall 0.336, F1-measure 0,342 NDCG 0.5
(Z. El Yebdri et al., 2021) [18]	Real-world datasets	Development of a hybrid, trust-based, context-aware post-filtering	MAE 0,79, RMSE 1

The pre-filtering method builds an appropriate 2D ($item\times users$) dataset using the contextual attributes that are most pertinent to the scenario. To determine the variance for a contextual attribute, compute the percentage of values in the array that match the specified values for each contextual attribute. The most relevant attribute is the one with the lowest variance. Depending on the most significant attribute found, we use the chosen value for that attribute. Then reduce the dataset based on the specified value to only include items with the most significant attribute as the selected value. CF is now applied to this compressed dataset. To predict the products, CF looks at the opinions of others with similar interests as you have had in the past. For our work, the Pearson Correlation Coefficient (PCC) is used to determine how similar one item is to other items. In this manner, we obtain the contextualized suggestion based on the attribute determined to be most significant to the user. Figure 1 shows the proposed approach architecture.

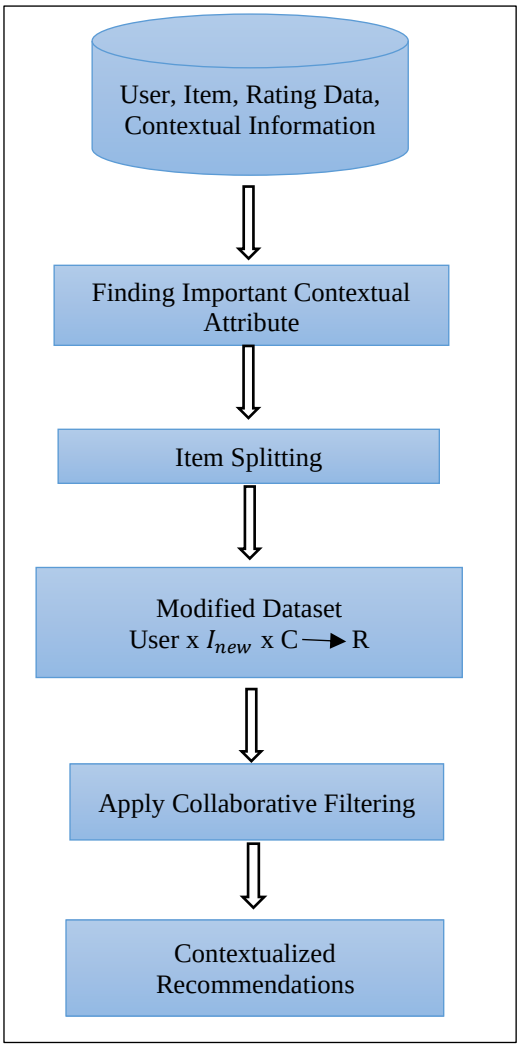


Figure 1: The proposed Contextual Pre-filtering.

3.1 Finding most important attribute and reduce the dataset

To identify the most important contextual attribute, we will compute the variance for each contextual attribute and then determine the most important attribute by taking the lowest variance for the contextual attributes.

The dispersion between the values in a dataset is measured as the variance. The dispersion, or variation, of data values increases with increasing variance. The following Equation (1) is used to compute the variance:

$$\sigma^2 = \frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{N} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where x_i each item in the dataset, $\bar{x}$ is the mean of all the dataset's values, and N is the number of items in the dataset.

After computing the variance for each contextual attribute, determine the most important attribute, i.e., the

contextual attribute with the lowest variance. Next, for the contextual feature that was determined to be the most significant, take the chosen value for that feature as ci, where i depend on feature. The dataset is reduced using a contextual pre-filter based on ci to only include records that have the value for ci, while all other values for user, product, and rating are left unchanged. The algorithm (1) shows contextual pre-filtering based on the most important attribute.

Algorithm (1): Contextual Pre-filtering Based on the Most Important Attribute
Input: Ratings for target user, LDOS-CoMoDa dataset. **Output:** Modified dataset.
Begin: **Step 1: Load** LDOS-CoMoDa dataset. **Step 2: Insert** user id. **Step 3: Get** contextual attribute for target user **Step 4: Calculate** the variances for each contextual attribute for target user. **Step 5: Sort** variances in descending order **Step 6: Choose low** variance as the most important attribute **Step 7: Calculate** the number of each value in most important attribute **Step 8: Sort** the number of each value in descending order **Step 9: Choose** the value with the most frequency **Step 10: Reduce** the dataset such that it only contains the most important components that have the value of the most important attribute **End**

Variance was chosen as a basic criterion for selecting attributes because it measures the extent of dispersion of values. Thus, we can know the user's preferences by measuring the variance for each contextual attribute within the user's preferences. Each contextual attribute has several values, which means that the contextual attribute with high variance has highly dispersed attribute values, while the contextual attribute with low variance has less dispersed attribute values. However, With the low variance, we can learn about user preferences by the most frequent value in this contextual attribute. Thus, we reduce the dataset to the basis of variance and the most frequently occurring value.

3.2 Collaborative filtering

Then, we utilize CF on the compressed dataset to predict the products that would interest customers currently based on customer product ratings. Equation (2), demonstrates how the item-based approach in the suggested system that uses PCC is required for calculating correlation between comparable goods. Utilizing the Equation (3), it is possible to determine a customer's predicted for a specific item i.

3.2.1 Building the rating matrix

After modifying the dataset, a data structure shown as a matrix was created to record the connections between various people and movies with their related ratings. From the modified dataset, extract UserID, ItemID, and Rating. The Rating Matrix (RM) can then be built. In RM, the columns correspond to the movie ID and the rows to the user ID. Each user's intersection with a movie had a cell value that held the corresponding rate that had been previously retrieved.

3.2.2 Measuring similarity

The next step after creating RM was to use the PCC to calculate the similarity between movies. The Items Similarity Matrix (ISM) was used in this model to store similarities between LDOS-CoMoDa movies. In this method, suggestions for the user are calculated by discovering objects that are related to other items. Equation (2) [19] has been used to show the PCC:

$$sim(k,l) = \frac{\sum_{u=1}^{m}(r_{u,k}-\bar{r}_k)(r_{u,l}-\bar{r}_l)}{\sqrt{\sum_{u=1}^{m}(r_{u,k}-\bar{r}_k)^2}\sqrt{\sum_{u=1}^{m}(r_{u,l}-\bar{r}_l)^2}} \quad \text{.....(2)}$$

Where m is the total number of people who rated both item k and item l, and $sim(k,l)$ denotes the degree of similarity between the two items. The average ratings for items k and l are $\bar{r}_k$ and $\bar{r}_l$, respectively; The terms $r_{u,k}$ and $r_{u,l}$respectively refer to the user u ratings of items k and l.

3.2.3 Prediction calculation

After the calculation of similarity, the prediction Equation (3) [20] was used to estimate the target user's prediction value and go on to the top N suggestions. A prediction on the product i of customer k is often made using the following formula:

$$P_{u,k} = \frac{\sum_{i=1}^{n}(r_{u,i}-\bar{r}_i)*sim(k,i)}{\sum_{i=1}^{n}|sim(k,i)|} \quad \text{.....(3)}$$

Where n is the total number of neighbors of item k, and $P_{u,k}$ is the prediction for user u on item k; By "$r_{u,i}$" we imply the user's evaluation of the item i, $\bar{r}_k$ is the average rating for the item k, $sim\,(k,i)$ represents the degree to which the item k and its neighbor i are similar; The term "$\bar{r}_i$" refers to the item i average rating.

In this way, we get the contextualized recommendation for the target user by implicitly extracting the preferences of the target user by applying the variance Equation (1) to contextual attributes, choosing the most important attribute, finding the most frequently used value in this attribute, and finally

modifying the dataset based on this value, then applying CF.

The main steps of the suggested algorithm are listed below:

Step 1: Download the LDOS-CoMoDa from the website.
Step 2: Inter user ID.
Step 3: Finding the most important attribute and reducing the dataset.

a. Calculate the variance for each contextual attribute for the target user.
b. Take the lowest variance.
c. Calculate the most frequent value from the attribute with the lowest variance.
d. Reduce the dataset based on the most frequency value.

Step 4: Apply CF

a. Calculate the similarity between movies by using the PCC equation.
b. Calculate predictions to create a list of recommendations for the target user.

4 Experimental results

The major goal of the experiments is to evaluate the degree of accuracy of the suggestions provided by the proposed approaches. The CPBCF model was evaluated using different values of the nearest neighbors, which allowed us to choose the top-k neighbors among users who had given the same item a rating. It is possible to further narrow the neighborhood so that users have rated the item in the same contexts if contexts are taken into account. This provides a recommendation computation that is particular to the context. Subsection 4.1 describes the experimental setting; Subsection 4.2 describes the data; and Subsection 4.3 presents the metrics for system evaluation. The results are presented in subsection 4.4.

4.1 Experimental setup

Table 2 lists the particular parameters of the experimental setting used in this article.

Table 2: Experimental environmental factors.

Category	Parameter
The operating system	Windows 10
A programming language	Python
CPU	Core i7
Memory	8GB

4.2 Dataset

A context-aware dataset for movie recommendations is called LDOS-CoMoDa. It was published in 2011 on the www.lucami.org website. The dataset consists of 1232 items and 2296 rating records from 121 individuals, together with contextual information. Table 3 contains a description of the contextual information in the LDOS-CoMoDa dataset. Each record has a total of 30 variables, including 4 user attributes, 11 item attributes, 12 contextual attributes, a user, an item, and a rating (an integer value between 1 and 5).

Table 3: Description of LDOS-CoMoDa Dataset.

Contextual variable	No. of category	Description
Time	4	1-morning, 2-afternoon, 3-evening, 4-night
Day type	3	1-working day, 2-weekend, 3-holiday
Season	4	1-spring, 2-summer, 3-autumn, 4-winter
Location	3	1-home, 2-public place, 3-friend's house
Weather	5	1-sunny/clear, 2-rainy, 3-stormy, 4-snowy, 5-cloudy
Social	7	1-alone, 2-partner, 3-friends, 4-colleagues, 4-parents, 6-public, 7-family
EndEmo	7	1-sad, 2-happy, 3-scared, 4-surprised, 5-angry, 6-disgusted, 7-neutral
Dominant Emo	7	1-sad, 2-happy, 3-scared, 4-surprised, 5-angry, 6-disgusted, 7-neutral
Mood	3	1-positive, 2-neutral, 3-negative
Physical	2	1-healthy, 2-ill
Decision	2	1-user's choice, 2-given by other
Interaction	2	1-first, 2-n-th

4.3 Evaluation metrics

The quality metrics for recommendation have been chosen as precision, recall, F1-measure, and Normalized Discounted Cumulative Gain (NDCG), while the quality measures for prediction have been chosen as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). In addition, the computational complexity of the system was analyzed. Table 4 shows the confusion matrix that was used to calculate the value.

Table 4: Confusion matrix [19].

	Relevant	Irrelevant
Recommended	True Positive (TP)	False Positive (FP)
Not Recommended	False Negative (FN)	True Negative (TN)

1) Precision: the most important metric for determining how effectively an RS is performing [22]. The top k recommendations that are relevant to the consumer are listed [23].

$$Precision = \frac{(TP)}{(TP+FP)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

The greater value of this relationship indicates that the RS has made a more accurate suggestion [24]

2) Recall: presents how many of the customer's favorite items he is interested in, as well as how many of those items the system has actually suggested to him [22].

$$Recall = \frac{(TP)}{(TP+FN)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

The higher number indicates that the RS has the ability to arrange the items according to relevance and move them to the top of the final list [24].

3) F1-measure: which is the harmonic mean of precision and recall, is used to evaluate the accuracy and effectiveness of the results generated by the recommended RS.

$$F1 - measure = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Due to accuracy and recall falling inside the [0, 1] range, an item with a high F1-measure value is considered to be more effective [24].

4) Normalized Discounted Cumulative Gain (NDCG): method to assess the grade of suggestions in order to calculate how much CARS learning has occurred. A list of suggested things with a greater NDCG value indicates that there are more related items placed higher in the list [12]:

$$NDCG = \frac{\sum_{k=1}^{n} G(u,n,k)D(k)}{\sum_{k=1}^{n} G*(u,n,k)D(k)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

where $G\ (u, n, k)$ is the gain associated with the k-th item in the ideal ranking of n size for u user, $G * \ (u, n, k)$ is the gain associated with the k-th item in the list L, and $D\ (k)$ is a discounting function [25].

5) Root Mean Square Error (RMSE): determines the probability of being incorrect when predicting a not-rated item for an active user [26]. This value must be lowered in order to more clearly illustrate the model's performance [27]. The equation is as follows:

$$RMSE = \sqrt{\frac{1}{N_P}\sum_{u,i}(P_{ui} - r_{ui})^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

N_P refers to the total number of predictions, and P_{ui} and r_{ui} are the actual and expected ratings of how likely it is that the user would choose item I [25].

6) Mean Absolute Error (MAE): is a statistic that measures how effectively recommendation algorithms predict outcomes and is used in a similar way to RMSE [28]. It may be calculated using the formula provided in:

$$MAE = \frac{1}{|T|}\sum_{r_{u,i} \in T} \left| r_{u,i} - \hat{r}_{u,i} \right| \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

Where $r_{u,i}$ and $\hat{r}_{u,i}$ are, respectively, used to indicate the actual and predicted ratings of the item for the user u [29][30]. With a smaller MAE, the RS is better able to predict ratings [24].

7) Computational Complexity: refers to the amount of time an algorithm or system takes to complete the required tasks based on the size of the input data. In recommender systems, time complexity is measured to analyze the efficiency during different stages, such as calculating the similarity matrix, generating recommendations, and ranking the results [31]. For the system used in this research, the total time complexity can be represented by the relationship:

$$O(n^2.m + m.n.k + n.logn) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (10)$$

Where n is the number of items, m is the number of users, and k is the number of neighbors used in the recommendations.

4.4 Results

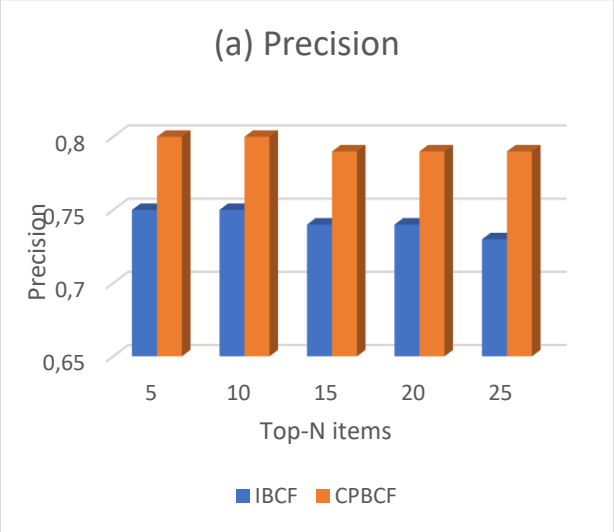
In the experiments, the performance of the suggested CPBCF with and without contextual pre-filtering was evaluated using the confusion matrix. The results showed that the suggested approach is capable of making product recommendations with higher precision, recall, and F1-measure than traditional IBCF. As for the NDCG scale, we notice a slight decrease in the results compared to the traditional method due to the reduction of data. For the suggested CPBCF model, Table 5 shows the precision, recall, F1-measure, and NDCG with different values of the nearest neighbors.

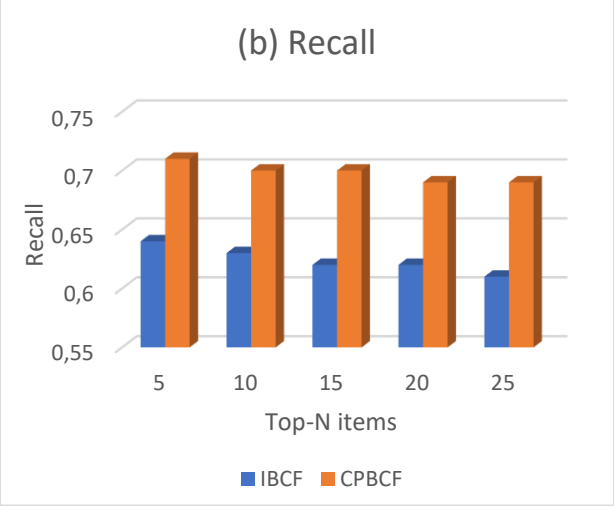
Table 5: Precision, Recall, F1-measure, and NDCG of RS with different number values.

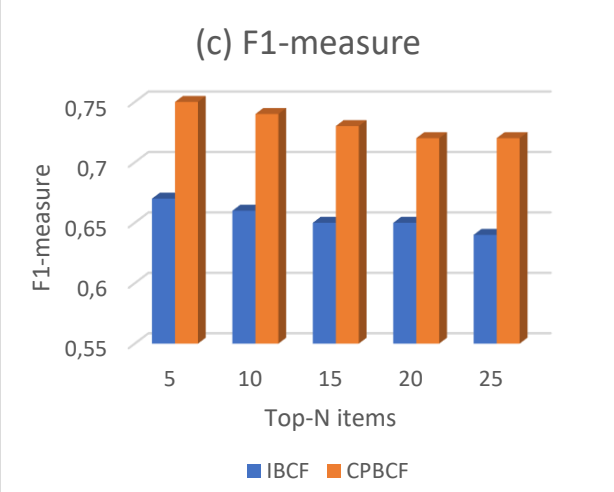
Measure	Methods	Number of different nearest neighbor				
		5	10	15	20	25
Precision	IBCF	0.75	0.75	0.74	0.74	0.73
	CPBCF	0.80	0.80	0.79	0.79	0.79
Recall	IBCF	0.64	0.63	0.62	0.62	0.61
	CPBCF	0.71	0.70	0.70	0.69	0.69
F1-massure	IBCF	0.67	0.66	0.65	0.65	0.64
	CPBCF	0.75	0.74	0.73	0.72	0.72
NDCG	IBCF	0.49	0.48	0.47	0.47	0.47
	CPBCF	0.23	0.24	0.24	0.24	0.27

The algorithms' precision, recall, F1-measure, and NDCG are displayed in Figure 2. All methods' precision,

recall, and F1-measure decrease while NDCG increases when the nearest neighbor grows.







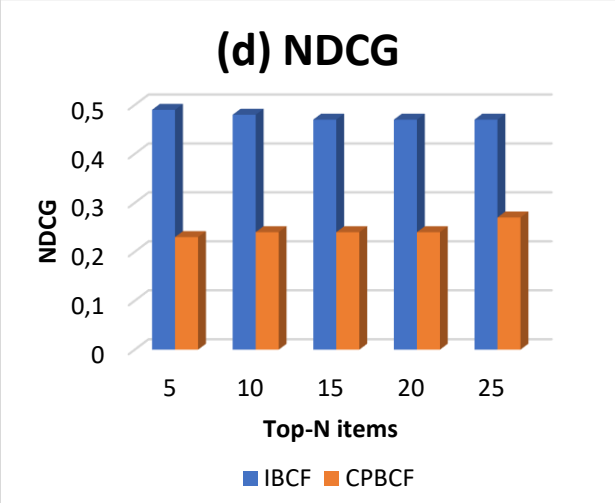


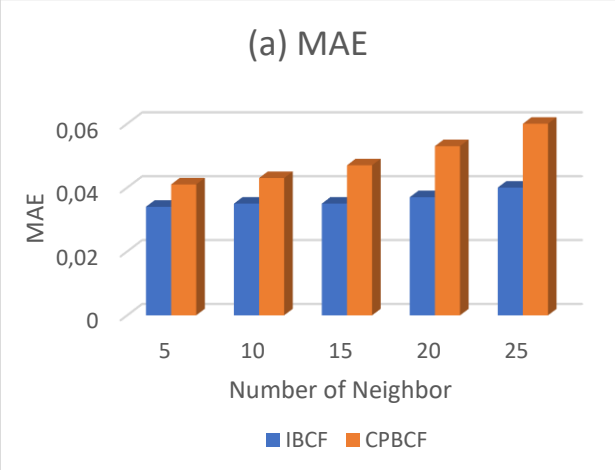
Figure 2: (a) Comparing Precision between IBCF with and without Contextual Pre-filtering, (b) Comparing Recall between IBCF with and without Contextual Pre-filtering, (c) Comparing F1-measure between IBCF with and without Contextual Pre-filtering, (d) Comparing NDCG between IBCF with and without Contextual Pre-filtering.

Some metrics are used to evaluate the suggested system. These measurements, known as MAE and RMSE, measure the variances between customer-suggested and actual preferences over time. According to the results of these measures, the CARS prediction results improve with decreasing error levels. Table 6 presents the MAE and RMSE results for the IBCF models with and without contextual pre-filtering prediction accuracy on the LDOS-CoMoDa dataset.

Table 6: MAE and RMSE of RS with different number values.

Measure	Methods	Number of different nearest neighbor				
		5	10	15	20	25
MAE	IBCF	0.034	0.035	0.035	0.037	0.040
	CPBCF	0.041	0.043	0.047	0.053	0.061
RMSE	IBCF	0.171	0.231	0.244	0.251	0.257
	CPBCF	0.232	0.261	0.319	0.357	0.393

The algorithms' MAE and RMSE are displayed in Figure 3. With k = 5, 10, 15, 20, and 25, different numbers of neighbors were used to evaluate the performance. We can see that the size of the neighborhood does have an impact on the accuracy of the forecast. The values of MAE and RMSE increased when the nearest neighbor increased.



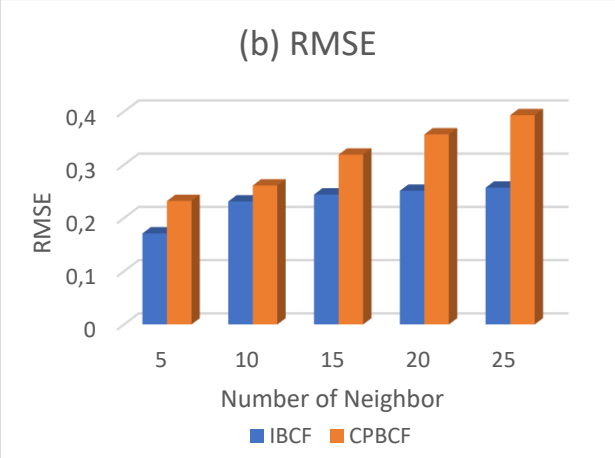


Figure 3: (a) Comparing MAE between IBCF with and without Contextual Pre-filtering, (b) Comparing RMSE between IBCF with and without Contextual Pre-filtering.

The complexity time of the efficiency analysis was measured during different stages, and the experimental results showed that the traditional method was more time-consuming compared to the CPBCF method, which benefited from data reduction before performing the calculations, which was positively reflected in the time performance of the system. Table 7 shows the complexity time with different values of nearest neighbor.

Table 7: Complexity time with different number values.

Measure	Methods	Number of different nearest neighbor				
		5	10	15	20	25
Complexity time	IBCF	4.925	5.057	5.12	5.716	5.868
	CPBCF	1.517	1.533	1.538	1.658	1.81

The complexity time of the methods is shown in Figure 4. Different numbers of neighbors were utilized for evaluating the performance with k = 5, 10, 15, 20, and 25. The use of CPBCF significantly improved the computational efficiency, making the method more scalable with big data.

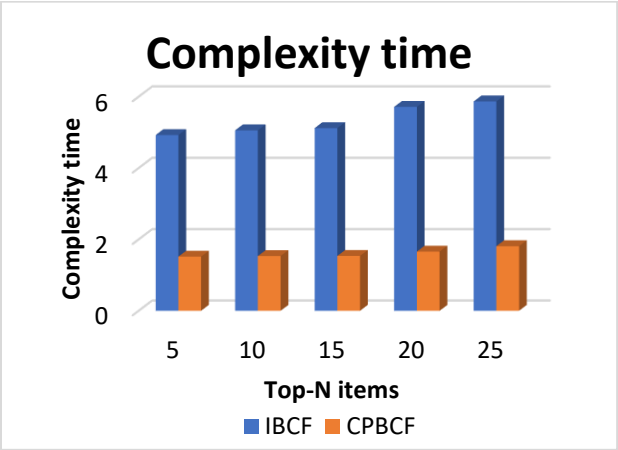


Figure 4: Comparing Complexity time between IBCF with and without Contextual Pre-filtering.

5 Discussion

In this work, the CPBCF model was created to incorporate contextual data into the recommendation process, hence addressing the issues associated with personalized suggestions. Compared to more conventional approaches, the results offer important new information about how well this approach enhances suggestion quality.

The results show that one of the most important steps in enhancing the recommendation process is pre-filtering the dataset using the variance of contextual factors. For the target user, the model successfully captures the most consistent relevant feature by determining which contextual characteristic has the lowest variance. The most frequent value of the attribute was used to filter the dataset, reducing noise and ensuring that only the most relevant data was used to provide recommendations.

The advantages of the suggested strategy were further demonstrated by the comparison between CPBCF and conventional IBCF. The enhanced precision, recall, and F1-measure of the CPBCF model demonstrate its ability to produce more accurate and pertinent recommendations. The pre-filtering procedure is responsible for this performance improvement since it ensures that the suggestions are based on an enhanced and contextually relevant dataset. These results support previous research, which highlights the importance of contextual information in recommendation systems.

A significant result from the tests was how neighborhood size affected the accuracy of recommendations. The F1-measure, precision, and recall were all adversely affected by the neighborhood size increase, even though it led to greater error rates (e.g., MAE and RMSE). Because they focus on individuals or objects that are more like the intended user, smaller, context-focused communities are consequently more successful. In addition, the NDCG results, although slightly lower, provide an interesting perspective. Reducing the dataset size due to the pre-filtering process resulted in a decrease in computational complexity, making the model more resource-efficient. This highlights

the balance between improving recommendation accuracy and maintaining system efficiency.

The suggested CPBCF model suggests that contextual pre-filtering can improve recommendation systems in a number of domains, including movie suggestions and personalized services. The model improves the quality of the information by using contextual variables to produce high-quality suggestions in a scalable and effective manner.

Despite its positive results, the CPBCF model's emphasis on variance and most common values may make it unable to capture all contextual dynamics, especially in datasets with a high degree of variability. Future studies should look at sophisticated techniques for identifying important contextual elements, such as2 mutual information, association-based selection, or feature importance measures.

6 Conclusions

Everybody deals with RSs on a daily basis. The rapid expansion of knowledge and information available online has increased the importance of developing efficient and effective RSs. The suggested CPBCF model employs CARS to accomplish personalization, with each user having a variety of contexts that describe the situation and environment around them. Our model works better than the conventional RS since it performs better when compared on the basis of precision, recall, and F1-measure. The confusion matrix was used to evaluate the effectiveness of the proposed CPBCF with and without contextual pre-filtering. According to the results, the recommended method has more precision, recall, and F1-measure than standard IBCF in making product suggestions. In addition, the NDCG results showed a slight decrease, which is a result of reducing the data size through initial filtering, which reduced the complexity time and increased the system efficiency. This highlights the balance between improving recommendation performance and system efficiency at the same time. The effectiveness of the CPBCF model was evaluated using various numbers of neighbors. The size of the neighborhood has an effect on forecast accuracy. When the nearest neighbor grew, the values of the MAE and RMSE rose while the values of the F1-measure, recall, and accuracy decreased.

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Semantic Feature Engineering with LSA-SVM for Cyberbullying Comment Classification on Instagram

Wulandari, Haerunnisya Makmur, Dewi Fatmarani Surianto*, Andi Akram Nur Risal, Nur Azizah Eka Budiarti, Satria Gunawan Zain, Abdul Wahid
Department of Computer Engineering, State University of Makassar, Makassar, Indonesia
E-mail: wlndry.nurdin@gmail.com, haerunnisyamakmur44@gmail.com, dewifatmaranis@unm.ac.id, andi.akram@unm.ac.id, nurazizah.ekabudiarti@gmail.com, satria.gunawan.zain@unm.ac.id, wahid@unm.ac.id
*Corresponding author

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Social media is now an essential part of everyday life, with Instagram being one of the most popular platforms and often utilized for various purposes, one of which is to increase popularity. However, the platform also often becomes a place where acts of violence and impoliteness in commenting increase, known as cyberbullying. To address the problem, detecting and classifying cyberbullying comments on Instagram is an important step in cyberbullying prevention. However, in text classification, several challenges need to be overcome to ensure the success of the model, such as polysemy, curse of dimensionality, and selection of text representation for feature extraction. Therefore, this study aims to implement a feature engineering technique using a hybrid approach that combines word weighting with TF-IDF and LSA method to reduce feature dimensionality and capture the semantic meaning of the data, with SVM used as a classifier to classify bullying and non-bullying comments. The results showed that the proposed method using feature engineering of the LSA matrix formed from the dataset of one of the classes, yielded a significant accuracy of 97%. In comparison, the conventional method with feature engineering using TF-IDF and the use of LSA matrix formed from the dataset of both classes only achieved an accuracy of 84%. This shows that the proposed method is more effective than the baseline approach.

Povzetek: Študija raziskuje klasifikacijo kibernetskega ustrahovanja v komentarjih na Instagramu z uporabo semantičnega inženiringa značilk s hibridnim pristopom LSA-SVM. Predlagana metoda združuje TF-IDF za uteževanje besed in LSA za zmanjšanje dimenzionalnosti značilk in zajemanje semantičnega pomena. Uporaba SVM kot klasifikatorja je pokazala, da ta pristop dosega dobro učinkovitost pri odkrivanju in klasifikaciji komentarjev kibernetskega ustrahovanja.

1 Introduction

Nowadays, digital technologies such as mobile device and social media are not just additional amenities, but have become an essential part of the daily lives of global citizens. More than 66% of the global population uses the internet, with active social media users reaching 5.04 billion by the start of 2024, representing a 5.6% increase in the past year [1]. Indonesia is one of the countries with the largest number of social media users, reaching 139 million users or equivalent to 49.9% of the total population [2]. Instagram has become one of the most popular social media platforms, with around 16.5% of internet users between the ages of 16 and 64 choosing Instagram over other platforms [1]. In Indonesia itself, there are around 106 million active users on the platform [3]. This phenomenon illustrates how social media, especially Instagram, has become an integral part of the daily lives of Indonesians.

Instagram as social media can be utilized to form an online community and share information, ideas, personal messages, and other content [4]. Users of this platform also utilize it for various purposes such as earning income as an endorser, improving existence, self-image, and popularity by sharing various types of content, in the hope of getting attention from other users through symbol responses, comments, or simply viewing [5]. However, this platform often becomes a place where acts of violence and incivility in commenting are on the rise [6]. Negative comments and hostile private messages are part of cyberbullying [7]. Based on a survey involving more than 10,000 young people aged 12 to 20 years old shows that cyberbullying is widespread, with nearly 70% of teens admitting to perpetrating abusive behavior towards others online and 17% claiming to have been victims of online bullying [8]. These cyberbullying behaviors can cause physical or psychological harm to their victims, including stress, social isolation, low self-esteem, anxiety, and depression [9] [10].

Table 1: Research components

No.	Component	Details
1	Technologies	Natural Language Processing (NLP), Machine Learning, Classification Models, and Cyberbullying Detection
2	Tools	Python, Scikit-learn and Jupyter Notebook
3	Algorithms	Support Vector Machine (SVM), TF-IDF, Latent Semantic Analysis (LSA), and Confusion Matrix
4	Case Studies	Cyberbullying detection from Instagram comments
5	Datasets	Instagram comment datasets related to cyberbullying and non-cyberbullying in the Indonesian language
6	Methods	Machine learning using the SVM algorithm for comment classification, feature extraction using a combination of TF-IDF and LSA, and evaluation using a confusion matrix

Cyberbullying on Instagram has become a common problem with serious consequences for individuals' mental health, therefore detecting and classifying cyberbullying comments is an important step in preventing the spread of this harmful behavior early on [11]. Machine learning-based classification models can be used to detect cyberbullying, as they have been proven efficient in predicting and detecting various types of data, including text data in the form of comments [12]. However, text classification faces several challenges such as word polysemy [12] [13], high data dimensionality that triggers overfitting [15], and text representations that affect the model's ability to understand text meaning [16]. Thus, the effectiveness of a classification model depends on the feature extraction results used, so the discovery of active feature extraction techniques has been the focus of many researchers to improve text classification performance [15]. Some of the simplest and most commonly used text representations for feature extraction are Bag of Words (BoW) and Term Frequency-Inverse Document Frequency (TF-IDF) [11] [17]. Although they can represent text well, these approaches tend to produce text representations that have large dimensions and limitations, such as BoW's inability to account for word order and TF-IDF's lack of semantic context [12].

Therefore, this study aims to identify comments containing elements of cyberbullying on social media, particularly on Instagram, by developing a machine learning-based classification model. To classify texts using machine learning, feature engineering techniques using hybrid approaches such as a combination of TF-IDF word weighting method and Latent Semantic Analysis (LSA) method are proposed to reduce the dimensionality of the features, while capturing the semantic meaning of the data. This research also investigates the effect of multiple feature engineering performed on classification performance, using features on the whole data as well as on one of the classes only. In summary, the main contribution of this research is the introduction of a feature engineering approach to improve the performance of the model, so that it can properly distinguish between cyberbullying and non-cyberbullying comments. The effectiveness of the proposed feature engineering technique is evaluated using confusion matrix using the Support Vector Machine algorithm as the classifier. This is important as it provides new insights into the problem of cyberbullying comments on social media and proposes a new method to address it. Table 1 summarizes the key components of this research, including the technologies, tools, algorithms, case studies, datasets, and methods used to achieve the research objectives.

2 Related works and novelty of the proposed work

Some previous research shows that there are various techniques developed to classify reviews or comments using machine learning algorithms. Several techniques and types of features have been used, including the use of the TF-IDF model as a feature for classification. One of the studies related to sentiment analysis on Shopee app reviews used TF-IDF as feature extraction, and Support Vector Machine (SVM) and Random Forest (RF) were used as classifiers. The results showed that the SVM model had a higher accuracy of 84.71% compared to Random Forest which was 82.21% [18]. A similar study used TF-IDF as feature extraction and Naive Bayes (NB) as a classifier for sentiment analysis of game products at Shopee, with an accuracy of 80.22% [19].

In addition, some studies focus on semantic modeling in the text as a feature extraction scheme. Several studies proposed semantic methods using LSA to improve model performance for detecting adverse drug reactions with four machine learning algorithms used as classifiers including SVM, NB, Logistic Regression (LR), and Artificial Neural Network (ANN) with two document representations used, namely Term Frequency (TF) and TF-IDF. The results showed that LSA as a feature with LR and ANN classifiers outperformed other algorithms with an accuracy of 82% [20] [21] [22]. Other studies used NB, SVM, and LR methods combined with LSA for sentiment

analysis of tweet replies on public figure accounts, with the highest accuracy on LR of 80.6% [23].

Various studies have also been conducted to identify and detect cyberbullying in recent years. One such study used Natural Language Processing (NLP) techniques and machine learning algorithms to detect cyberbullying in Bangla and Bangla Romanization texts from YouTube comments, where the SVM method achieved 76% accuracy for the Bangla dataset, while Multinomial Naive Bayes (MNB) achieved 84% accuracy for the Bangla Romanization dataset and 80% for the combined dataset [24]. Another study performed cyberbullying classification from Twitter data using SVM method as a classifier and Information Gain (IG) as a feature selection technique, by exploring the effect of various SVM parameters and various IG selection thresholds [25]. There is also research applying machine learning techniques using three datasets to detect cyberbullying, where SVM achieved the highest accuracy of 92% [26].

Furthermore, research that proposed an approach to detect cyberbullying in Roman Urdu texts by addressing the colloquial and non-standard variations of users' writing styles on social media, using several feature extraction techniques such as N-Gram, hybrid n-gram, and TFIDF weighting. Experimental results showed that SVM with hybrid N-gram embedded features achieved the highest average accuracy of about 83% [27]. In the following, cyberbullying identification using SVM, LR, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Bidirectional LSTM, and Bidirectional Encoder Representations from Transformers (BERT) methods. The results showed that BERT achieved the highest F1-score, which was 94% for the Twitter dataset, 91% for the Wikipedia dataset, and 92% for the Formspring dataset [28].

The next research is the classification of cyberbullying comments from tweets on Twitter using the ANN method where the classification results were improved using Deep Reinforcement Learning (DRL), resulting in an average increase in classification accuracy of 80.69% [29]. Another study was to detect cyberbullying in tweets from Twitter using TF-IDF feature extraction and Naive Bayes and SVM algorithms for the classification process, where the accuracy of Naive Bayes was 52.70% while SVM reached 71.25% [30].

Table 2: Related works and proposed method

Ref. (Year)	Domain (Language)	Class (Data Source)	Method (Accuracy)	Limitations/Descriptions
[17] (2023)	Shopee App Reviews (Indonesian)	Positive and negative (Kaggle)	TF-IDF+SVM (82.21%) TF-IDF+RF (84.71%)	Limited to Bag-of-Words and TF-IDF features; lacks semantic understanding or contextual embeddings.
[18] (2021)	Game product reviews (Indonesian)	Positive, neutral, negative (Shoppe)	TF-IDF+Naive Bayes (80,22%)	Did not compare Naive Bayes with other advanced models or integrate semantic/contextual embeddings.
[19][20] (2021)	Adverse Drug Reactions (English)	Positive negative (Previous research)	TF+LSA+LR (82%) TF-IDF+LSA+SVM (80%)	Did not utilize advanced techniques like word embeddings or neural networks, limiting performance in complex semantic tasks.
[21] (2024)	Adverse Drug Reactions (English)	Positive and negative (Previous research)	TF+ANN (82%) TF+LSA+ANN (85%) TF-IDF+LSA+ANN (83%)	Did not employ advanced embedding techniques or architectures like transformers, which could enhance contextual understanding.
[22] (2022)	Public Figure (Indonesian)	Positive, neutral, negative (Twitter)	TF-IDF+LSA+NB (78.6%) TF-IDF+LSA+LR (80.6%) TFIDF+LSA+SVM (80.4%)	The addition of LSA reduced model performance; lacked exploration of hybrid or ensemble methods for improvement.
[23] (2021)	Cyberbullying (Bangla and Romanized Bangla)	Bullying and not-bullying (Youtube)	TF-IDF+SVM (76%) - Bangla TF-IDF+MNB (84%) - Romanized TF-IDF+MNB (80%) - Bangla and Romanized	Relied solely on TF-IDF without addressing deeper contextual relationships or semantic nuances between words.

Ref. (Year)	Domain (Language)	Class (Data Source)	Method (Accuracy)	Limitations/Descriptions
[24] (2020)	Cyberbullying (Indonesian)	Bullying and not-bullying (Twitter)	TF-IDF+SVM (75%) TF-IDF+IG+SVM (76.66%)	Dependency on TF-IDF and IG limited the feature set, potentially missing critical semantic patterns.
[25] (2022)	Cyberbullying (English)	Bullying and non-bullying. (Previous research)	Random Forest (91%) Naïve Bayes (87%) SVM (92%)	Did not fully explore deep contextual embeddings or advanced neural architectures for nuanced text understanding.
[26] (2023)	Cyberbullying (Roman Urdu)	Bullying and non-bullying. (Social media)	TF-IDF+Hybrid N-gram+SVM (83%)	High-dimensional feature space due to N-gram combination; lacked deeper semantic feature extraction.
[27] (2022)	Cyberbullying (English)	Positive negative (Twitter, Wikipedia, Formspring)	BERT (94%) - Twitter BERT (91%) - Wikipedia BERT (92%) - Formspring	Fine-tuning on the BERT model requires extensive training time and significant computational resources.
[28] (2021)	Cyberbullying (English)	Bullying, and non-bullying (Twitter)	Deep Reinforcement Learning (80.69%)	Integrating ANN with DRL for improved classification. However, it adds complexity in implementation and processing time, limiting scalability.
[29] (2020)	Cyberbullying (English)	Bullying and non-bullying. (Twitter)	TF-IDF+NB (52.70%) TF-IDF+SVM (71.25%)	Relatively low accuracy; lacked advanced feature engineering and semantic understanding.
Proposed Method	**Cyberbullying (Indonesian)**	**Bullying and non-bullying. (Instagram)**	**(Feature Engineering TF-IDF + LSA) + SVM (97%)**	**Outperforms previous methods in accuracy and balance**

As explained in the previous section, many techniques have been applied by researchers to solve classification problems. The various techniques are analyzed and compared based on their performance and the type of dataset used. Table 2 presents a summary of various machine learning approaches and techniques applied, as well as the proposed method.

Several previous studies have shown that NLP approaches can be applied to detect and classify texts, especially in the context of cyberbullying. However, most of these studies focus on the English language or employ single approaches, such as TF-IDF or standard machine learning algorithms, which often fail to capture the complex semantic meanings in textual data. Additionally, high-dimensional feature representations frequently lead to overfitting issues. Therefore, the novelty of this study, as summarized in Table 2, lies in proposing a hybrid approach that integrates TF-IDF and LSA to capture semantic context and reduce feature dimensionality while exploring the impact of feature engineering techniques on the performance of SVM-based classification models. This research makes a significant contribution to the development of cyberbullying classification models in the Indonesian language, an area that remains underexplored. Evaluation results demonstrate that the proposed approach is more effective than the baseline, achieving high performance in detecting comments containing cyberbullying.

3 Methodology

This section explains the various stages involved in completing the research on cyberbullying comment classification using the proposed method. These stages include data collection, data annotation, preprocessing, feature engineering, classification model, and evaluation. The scheme of the stages of this research can be seen in Figure 1.

3.1 Data collection

The dataset used was obtained from several sources with a total of 2100 data shown in Table 3. The data used in this study were Instagram comments taken from the posts of

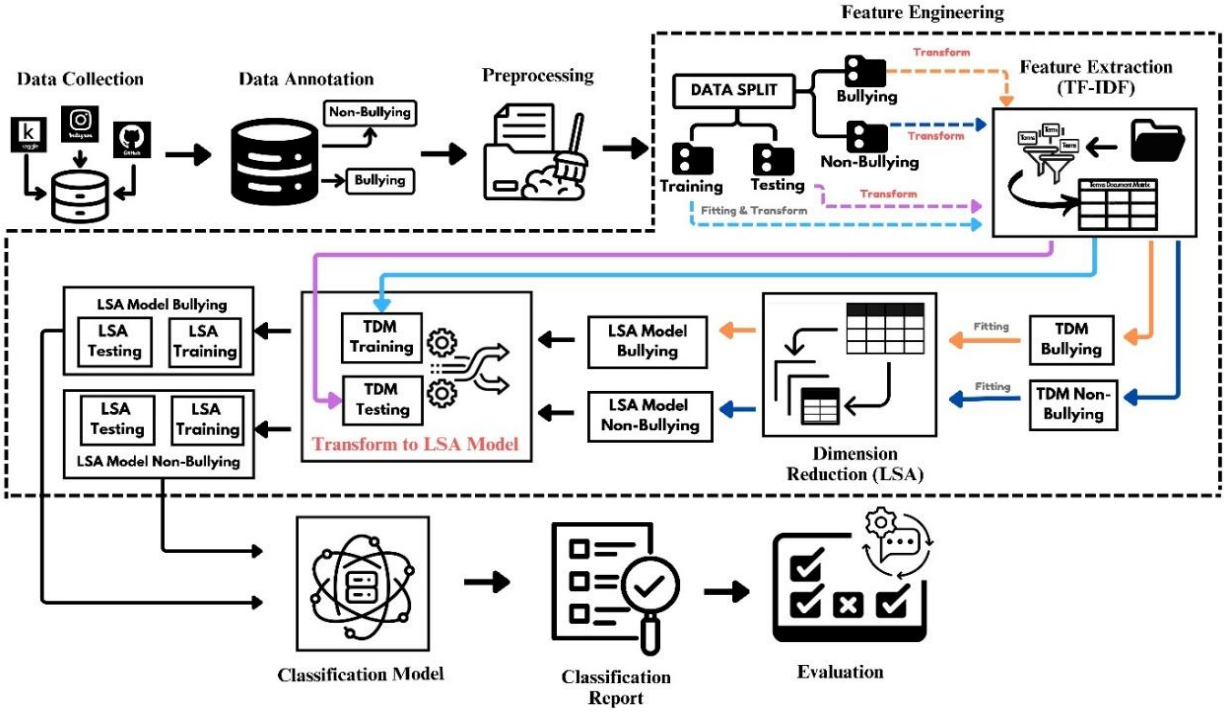


Figure 1: Stages of the proposed research method

several artists in Indonesia, as cyberbullying which includes negative comments, personal attacks, and ridicule, is a common problem that often targets celebrities and influencers [31]. This data collection technique was carried out to obtain a dataset that is representative of the phenomenon of cyberbullying on social media, particularly within the social context of Indonesia. This relevant data supports the training of the model to more accurately identify and classify bullying comments.

Table 3: Dataset distribution

Source	Number of Comments	
	Bullying	Non-Bullying
Instagram	525	525
Kaggle [32]	325	325
GitHub [33]	200	200
Total	1050	1050

3.2 Data annotation

Annotation on the dataset aims to provide information related to the category or class by each data, where in this study it consists of two classes, namely bullying and non-bullying comments. Determination of annotation was done by analyzing the comments based on their characteristics as in Table 4 [34]. This process is crucial to ensure accurate data labeling, enabling the machine learning model to better recognize specific patterns in each category, thereby supporting more reliable classification.

Table 4: Characteristics of bullying and non-bullying comments

No.	Bullying	Non-Bullying
1.	Contains insults or harassment	Contains support or appreciation
2.	Disrespectful or contains abusive language	Not condescending and not scornful

3.3 Preprocessing

Preprocessing is done to clean and improve the structure of the comment text so that it is more easily processed by the algorithm or model used [35] [36]. This stage is the most important initial step in classification, where the combination of preprocessing techniques can affect the classification performance results [37]. By cleaning the text of irrelevant elements enables the model to concentrate more effectively on essential information required for classification. The preprocessing steps used in the research include casefolding, regex, stopword removal, and stemming. The data preprocessing stages can be seen in Figure 2.

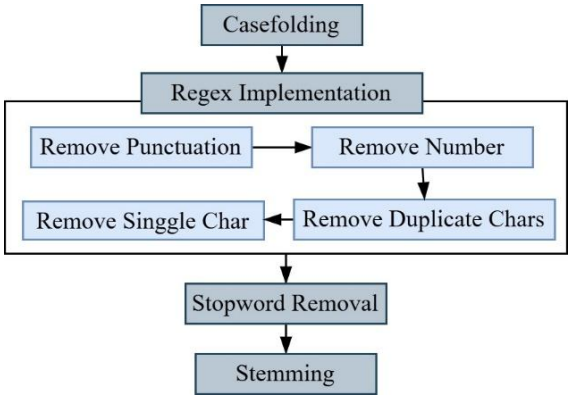


Figure 2: Data preprocessing stages

In this stage of text preprocessing, several libraries available in the Python programming language were used. First, to perform casefolding, the lower () function was used to convert all letters in the text to lowercase. Next, the regular expressions (regex) library was used to implement text processing based on the specified pattern. As for removing common words (stopwords) in Indonesian, the Natural Language Toolkit (NLTK) library was used by retrieving the list of available stopwords. To perform stemming (removal of prefixes and suffixes) in Indonesian, the Sastrawi library developed specifically for this language was used.

3.4 Feature engineering

Feature engineering is the process of extracting meaning from raw data by converting text into numerical values, which aims to improve efficiency and consistency in text classification using machine learning approach [38]. This technique is necessary to capture patterns and characteristics of relevant text data, enabling the model to better understand the relationships between words. In this study, the feature engineering technique used involves two main methods, namely feature extraction using TF-IDF and dimensionality reduction with LSA. The algorithm or steps of the feature engineering process along with their descriptions can be found in Table 5 below.

Table 5: Algorithm of the feature engineering

Algorithm: Feature Engineering for Text Classification using TF-IDF and LSA	
Step 1: Data Preparation	
1.	**Input:** Preprocessed dataset
2.	**Process:** • Categorize text data into bullying and non-bullying groups to facilitate the extraction of more specific features. • Split the dataset into training and testing subsets with a 70:30 ratio using train_test_split to ensure the model is trained on the majority of the data (70%) and tested on the remaining data (30%), allowing for an objective evaluation of the model's performance.
3.	**Output:** Training and testing datasets for both bullying and non-bullying categories
Step 2: Feature Extraction using TF-IDF	
1.	**Input:** Training and testing text data
2.	**Action:** • Use TfidfVectorizer to convert text into numerical representations • Training Phase: Apply fit_transform () on the training set to generate Term-Document Matrix (TDM). • Testing Phase: Apply transform () on the test set using the trained TF-IDF model for consistency • Bullying and Non-Bullying Datasets: Perform the same transformation process on the bullying and non-bullying datasets to create feature representations specific to each category and enhance the model's ability to recognize patterns within each category.
3.	**Output:** TDM from the training set, testing set, bullying dataset, and non-bullying dataset.
Step 3: Dimensionality Reduction using LSA	
1.	**Input:** TDM from TF-IDF for the training and testing sets, as well as the bullying and non-bullying datasets.
2.	**Action:** • Apply TruncatedSVD to reduce the dimensionality while preserving important information in the data. • **Fit the LSA model:** Apply the LSA model to the bullying and non-bullying TDM datasets using fit() with 500 topics on different TruncatedSVD models to capture relevant patterns and topics from bullying or non-bullying data. This will make the model more effective in identifying differences between the two and generating better dimensional representations. • **Transform Data:** Use the trained LSA model, both with the bullying and non-bullying datasets, to transform the TDM of the training and testing sets into lower-dimensional representations through the U matrix from Singular Value Decomposition (SVD). This matrix is then used as features in the classification model to improve the efficiency and accuracy of predictions.
3.	**Output:** • Matrix U on the training set and testing set using the LSA model trained with the Bullying TDM.

Algorithm: Feature Engineering for Text Classification using TF-IDF and LSA	
	• Matrix U on the training set and testing set using the LSA model trained with the Non-bullying TDM.

3.4.1 Feature extraction

Feature extraction using the Term Frequency-Inverse Document Frequency (TF-IDF) method aims to transform text into a numerical representation in the form of a Term-Document Matrix (TDM), allowing the model to understand the data quantitatively. The feature extraction process began by splitting the dataset into two separate subsets, one for training the model (training set) and one for testing the model (testing set), with a proportion of 70:30 using the `train_test_split` function from the Scikit-learn library. In addition, the dataset was further categorized into bullying and non-bullying datasets, for more specific feature extraction. This division helped to understand and identify the unique characteristics of each comment type and improved the model's performance in detecting and classifying cyberbullying more effectively.

The TF-IDF method was used to give weight to words in a document based on their frequency of occurrence, both in the document itself and in the entire corpus, thus enabling the identification of more meaningful and relevant words. The mathematical equations for calculating the weight of words in a document using TF-IDF can be found in equations (1), (2), and (3) as follows [39].

$$tf_{t,d} = \begin{cases} 1 + log_{10}\, tf_{t,d}, & if\ tf_{t,d} > 0 \\ 0 & otherwise \end{cases} \quad (1)$$

$$idf_t = log_{10} \frac{N}{df_t} \quad (2)$$

$$w_{t,d} = tf_{t,d} \times idf_t \quad (3)$$

Description:
$tf_{t,d}$ = frequency of occurrence of word t in document d
N = number of documents
idf_t = number of documents that contain t
$w_{t,d}$ = TF-IDF weight

In this research, the feature extraction process used `TfidfVectorizer` from the Scikit-learn library to transform text data into TF-IDF representation in TDM form. The feature extraction process in this study involved fitting and transforming the data using the TfidfVectorizer with fit_transform () function on the training set. After that, the transform () function of TfidfVectorizer was applied using the testing set, to transform the data into the same TDM format as learned from the training set. A similar transformation process was also applied to the bullying dataset and the non-bullying dataset.

3.4.2 Dimensionality reduction

Dimensionality reduction was performed using the Latent Semantic Analysis (LSA) method, which can extract and represent the hidden meaning of documents in a text corpus by reducing the dimensionality of the data. The application of LSA at this stage aims to enhance the model's understanding of the semantic context of the text by reducing dimensional complexity, allowing the model to capture deeper relationships between words, even if those words do not frequently appear together in the same document. This method utilized Singular Value Decomposition (SVD) to reduce the number of dimensions of the TDM used as LSA input. This process produced three new matrices from the SVD decomposition, with the mathematical equation that can be seen in equation (4) below [40].

$$A_{m,n} = U_{m,m} \Sigma_{m,n} \, (V^T)_{n,n} \quad (4)$$

Description:
$A_{m,n}$= m × n matrix (m documents, n terms)
$U_{m,m}$ = m × r matrix (m documents, r concepts)
$\Sigma_{m,n}$ = r × r matrix (value of each concept)
$(V^T)_{n,n}$ = n × r matrix (n terms, r concepts)

In this research, the LSA method was implemented using `TruncatedSVD` from the scikit-learn decomposition library. The implementation began with fitting using the fit() function on the TDM generated from the `TfidfVectorizer` transformation on the bullying dataset and non-bullying dataset. As a result, two LSA models were obtained, namely bullying and non-bullying LSA models, with 500 topics defined for comment classification. These models were then used to transform the TDM training set and testing set into the LSA model. From the results of the LSA model transformation, the matrix (U), which represented the relationship between documents and latent concepts in the dataset, then was used as a feature for the classification process.

3.5 Classification model

Classification models were developed using the Support Vector Machine (SVM) algorithm, which can be used in machine learning for classification. The purpose of applying the SVM algorithm is to leverage SVM's ability to handle complex and non-linearly separable data, with the Radial Basis Function (RBF) kernel chosen for its capability to capture non-linear relationships in the data. [41]. The SVM model was implemented using the scikit-learn library by utilizing the `SVC` class. The classification model development process involved exploring various feature engineering scenarios to identify the most optimal features used in the formation of the classification model. The feature engineering scenarios explored in the classification model building can be found in Table 6 below.

Table 6: Feature engineering scenarios

Scenario	Classification feature formation			
	TF-IDF		LSA	
	Bullying training set	Non-bullying training set	Bullying dataset	Non-Bulling dataset
1	✓	✓	-	-
2	✓	-	-	-
3	-	✓	-	-
4	✓	✓	✓	✓
5	✓	✓	✓	-
6	✓	✓	-	✓

From Table 6 above, there are six scenarios performed to form classification features based on the subset of data used. The aim of each scenario is to generate features representing the bullying class, the non-bullying class, or both. The results of the feature formation from each scenario will be used to transform or extract features from the training and testing data so that the data can be used to train and test the classification model.

3.6 Evaluation

The performance measurement of the model is based on data from the confusion matrix, which aims to provide a comprehensive overview of how the model classifies comments into bullying and non-bullying categories. By calculating accuracy, precision, recall, and F1-Score, the evaluation is conducted on various aspects of the model's quality, including its ability to correctly identify bullying comments (precision), recognize all existing bullying comments (recall), and balance between the two (F1-Score). The use of this confusion matrix allows for a deeper evaluation of the model's strengths and weaknesses, providing clearer insights into areas that need improvement. The form of the confusion matrix is presented in Table 7.

Table 7: Confusion matrix

		Prediction	
		TRUE	FALSE
Actual	TRUE	True Positive	False Negative
	FALSE	False Positive	True Negative

The formulas for calculating accuracy, precision, recall, and F1-Score can be seen in equations (5), (6), (7), and (8) respectively [42].

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} \quad (5)$$

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

$$F1\text{-}Score = \frac{2 \times precision \times recall}{precision + recall} \quad (8)$$

Table 8: Preprocessing results

No.	Preprocessing Stage	Bullying	Non-Bullying
1	Original data	Laki skrng kan pada begitu bnyk nya😂 seramm yaa.. Modal tampang aja..eeh numpang hidup sama istri😁 lebih baik menjanda😊	Dari kasus yg seperti ini.. Bahwa Sampai kapanpun.. Rezeki Halal itu udah yg paling Bener.. Meski Tak Banyak.. Namun Berkah 🙏❤
2	Casefolding	laki skrng kan pada begitu bnyk nya😂 seramm yaa.. modal tampang aja..eeh numpang hidup sama istri😁 lebih baik menjanda😊	dari kasus yg seperti ini.. bahwa sampai kapanpun.. rezeki halal itu udah yg paling bener.. meski tak banyak.. namun berkah 🙏❤
3	Regex	laki skrng kan pada begitu bnyk nya seram ya modal tampang aja eh numpang hidup sama istri lebih baik menjanda	dari kasus yg seperti ini bahwa sampai kapanpun rezeki halal itu udah yg paling bener meski tak banyak namun berkah
4	Stopword removal	laki skrng bnyk seram modal tampang aja eh numpang hidup istri menjanda	rezeki halal udah bener berkah
5	Stemming	laki skrng bnyk seram modal tampang aja eh numpang hidup istri janda	rezeki halal udah bener berkah

4 Results and discussion

Data pre-processing is an important step as raw data obtained from various sources is often not in a form that is ready for use. Therefore, the preprocessing stage is necessary to obtain a more structured dataset to produce informative features. The following is an example of the results of the preprocessing stage in Table 8.

In the casefolding stage, the letters in the text were all converted into lowercase letters. Then, the regex stage went through several stages of the process, namely the removal of punctuation marks, numbers, double characters, and single characters. In the example above, it can be seen that all full stops in the text are removed and the word "seramm" is changed to "seram". Then, common words that often appear in the text were removed in the stopword removal stage from the NLTK corpus such as the words "pada", "sama", "lebih", "dari", "paling", and others, resulting in a shorter sentence than before. In the stemming stage, the word was converted to its base word form such as "menjanda" was converted to "janda". As for the non-bullying example sentence, there was no word change because all words were already in their base word form.

After preprocessing, the dataset was divided into two data partitions for classification model building. A total of 70% of the 2100 data was allocated as training data, while the rest became testing data. In Figure 3, there is an even distribution in each data partition, with the amount of data divided proportionally for each class without significant differences.

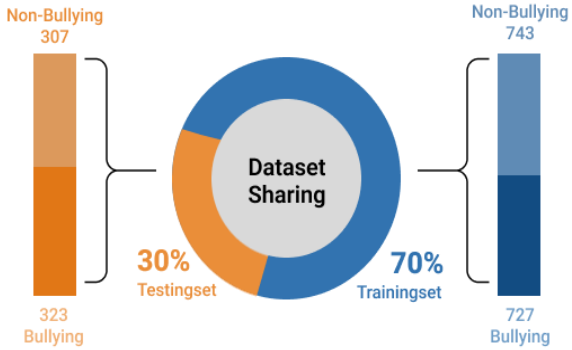


Figure 3: Distribution of dataset sharing

In developing the classification model, a features engineering stage was carried out which involved feature extraction using the TF-IDF and LSA methods. By using both feature extraction methods, several feature engineering scenarios were carried out for the formation of classification features to produce an optimal classification model. In Table 9 below are the classification model performance results based on the features engineering scenarios in Table 6.

Table 9: Results of research scenario classification

Scenario	Accuracy (%)	Precision (%)		Recall (%)		F1-Score	
		Bullying	Non- Bullying	Bullying	Non- Bullying	Bullying	Non- Bullying
Scenario 1	84	82	87	89	79	85	83
Scenario 2	84	81	89	91	77	86	83
Scenario 3	82	83	81	81	82	82	81
Scenario 4	84	80	90	92	76	86	82
Scenario 5	97	95	100	100	94	97	97
Scenario 6	97	100	95	95	100	97	97

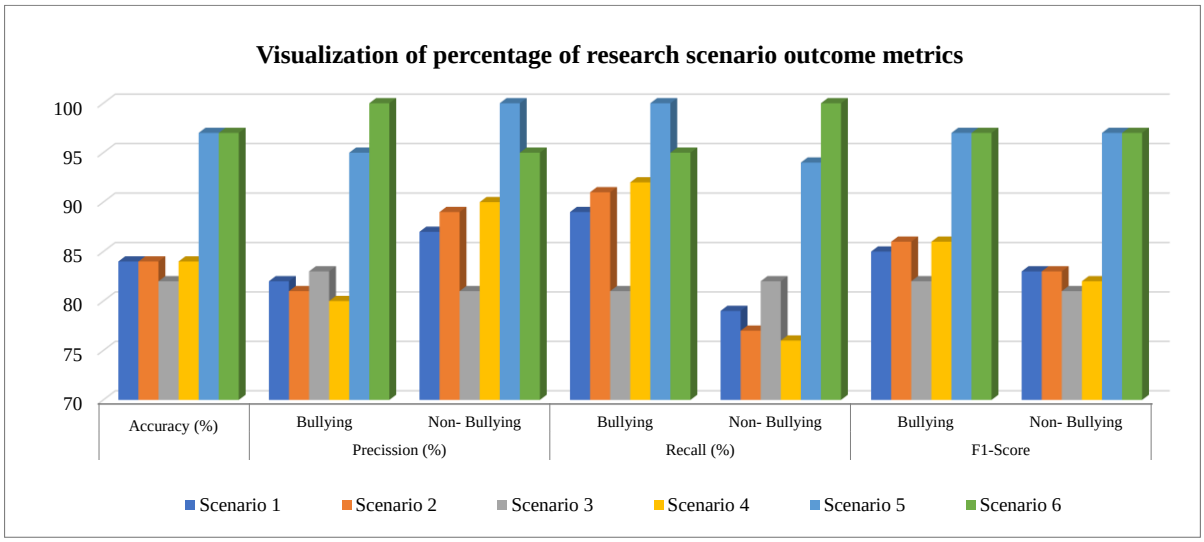


Figure 4: Research scenario results diagram

Based on the results obtained in Table 9, in scenario 1, the classification features were generated from weighting the documents using the TF-IDF matrix trained with the entire train data. Although the classification model had good precision in identifying the Bullying and Non-Bullying categories, there was a significant difference in the recall rate between them. In scenarios 2 and 3, the training process only used one of the classes to form the classification features based on the TF-IDF matrix. However, the results showed that in scenario 2 where the classification features were formed from the TF-IDF of the bullying class, there was a decrease in the non-Bullying class compared to the previous scenario. Otherwise, in scenario 3, the classification features obtained from the TF-IDF matrix of the non-bullying class showed a stable and consistent performance of the model in classifying texts for both classes, but a significant decrease in performance compared to scenarios 2 and 3.

The results of scenarios 1, 2, and 3 still showed low performance in distinguishing bullying and non-bullying classes. This was due to the limitation of the model that used TF-IDF as feature extraction which has not been able to handle synonyms, polysemy, and hidden meanings in the text as LSA does. [43]. Therefore, another features engineering scenario applying the LSA method was required, such as in scenarios 4, 5, and 6. In those scenarios, the LSA method was implemented after word weighting using the TF-IDF matrix to obtain the U matrix from SVD result which was used as a classification feature. The TDM used as LSA input in this scenario was the TF-IDF matrix trained using the entire train data. In scenario 4, the classification features were obtained from the LSA method trained using the TDM from the training set, but no performance improvement occurred.

Based on the diagram in Figure 4, scenario 5 which was the proposed feature engineering technique using the LSA method trained using TDM from the bullying class dataset, showed excellent performance with accuracy, precision, recall, and F1-Score values reaching 100% for both categories. Scenario 6 which was also a feature engineering technique proposed using TDM from the non-bullying class dataset for LSA modeling, yielded almost identical performance to scenario 5. Although Scenarios 5 and 6 had similar performance, Scenario 5 had slightly lower recall for the non-Bullying category, while Scenario 6 had slightly lower precision and F1-Score for the Bullying category. Therefore, it can be concluded that the proposed method of LSA model building using data from only one of the classes showed excellent accuracy results when used for classification model training.

Although LSA was expected to improve accuracy by capturing semantic meaning, Figure 4 shows that in scenario 4, the result is almost lower than other TF-IDF scenarios. This was because the data used had a phenomenon of lexical ambiguity where there were 25% of the same terms appeared in both classes, but the terms had different meanings. The terms that appeared together in two classes can be seen in Figures 5 and 6 below.

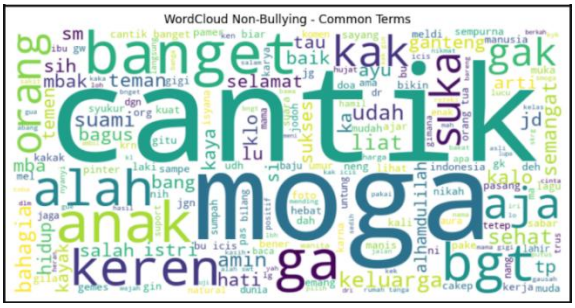


Figure 5: Wordcloud non-bullying terms found in bullying class



Figure 6: Wordcloud bullying terms found in non-bullying class

Based on Figures 5 and 6, the word "cantik" which means physically attractive or having a beautiful appearance is usually used in a positive context. In Figure 5, it can be seen that the word "cantik" appears frequently in non-bullying class. However, this word also appears in the bullying class, as shown in Figure 6, but the frequency is not too much. Another example is the word "ganteng" which also has a positive meaning in the non-bullying class, but this word is also found in the bullying class. Based on this, the application of the LSA method in both classes caused the phenomenon of lexical ambiguity, which is the same word, but has different meanings in different contexts [44]. Lexical ambiguity resulted in mixed semantic information which made it difficult for the model to learn the true meaning of the word "cantik" or "ganteng" when used in the context of satire (bullying) and a positive context (non-bullying). The phenomenon of mixed semantic information can also be seen from the topics generated in scenario 6 with the LSA model formed using the two classes dataset presented in Table 10 below.

Table 10: Example terms on topics in scenarios 4, 5, 6

Scenario Topic 4	Scenario Topic 5	Scenario Topic 6
[‘suka’, ‘sih’, ‘bgt’, ‘udah’, ‘hidup’, ‘anjing’, ‘penjara’, ‘sehat’, ‘cakep’, ‘sarah’]	[‘ganteng’, ‘doang’, ‘ga’, ‘muka’, ‘udah’, ‘anjing’, ‘jelek’, ‘gak’, ‘cari’, ‘modal’]	[‘cantik’, ‘banget’, ‘masya’, ‘alah’, ‘moga’, ‘kak’, ‘bgt’, ‘keren’, ‘sehat’, ‘icis’]

Based on Table 10, in scenario 4, it can be seen that there are positive terms such as ‘suka’, ‘hidup’, ‘sehat’ and ‘cakep’, which are quite representative of the non-

bullying class. But within the same topic, there are also some blasphemous words such as 'anjing' and 'penjara' which represent the bullying class. This created confusion of meaning for the model, as terms that usually represent one class are mixed into one topic. When these conflicting terms appeared together, the model struggled to determine the true context and sentiment of the text. For example, the word 'suka' usually carries a positive connotation, associated with compliments or harmless comments. Otherwise, the word 'anjing' in this context is a slur with strong negative connotations, often used to insult or demean someone. This combination of conflicting terms in one topic caused the model to struggle to classify the text correctly, as the terms it received were ambiguous and conflicting. This situation is an example of mixed semantic information, where the text contains various conflicting elements of meaning.

As for the topic of Scenario 5 found in Table 10, the terms generated almost all mean bullying. For example, words like 'anjing' and 'jelek' strongly reflect bullying content. Although there is the word 'ganteng' which connotatively can be categorized as non-bullying terms, the number was very small or only appeared a few times. With such a strong dominance of bullying terms in this topic, the LSA model did not experience any confusion in capturing the semantic meaning of the word, so the LSA model was able to clearly identify that the overall context of the topic was more inclined towards bullying despite some exceptions.

Therefore, experimenting with training LSA in a single class showed effective results as the model could learn the meaning of words more effectively without experiencing confusion from different meanings in other contexts. [45]. This allowed the LSA to better capture the special characteristics of the class compared to using two classes, due to noise reduction i.e. noise due to lexical ambiguity. Thus, Scenario 5 and Scenario 6 showed very high model performance with accuracy and F1-Score reaching 97% for both Bullying and Non-Bullying categories. The scenario results showed that the classifier was better able to recognize patterns from the data when the classification features from the LSA were sourced from one class, even though each used an LSA implementation for classification feature formation. The confusion matrix of the two scenarios can be seen in Tables 11 and 12.

Table 11: Confusion matrix of scenario 5 classification results

		Prediction	
		Bullying	**Non-Bullying**
Actual	**Bullying**	323	0
	Non-Bullying	18	289

Table 12: Confusion matrix of scenario 6 classification results

		Prediction	
		Bullying	**Non-Bullying**
Actual	**Bullying**	306	17
	Non-Bullying	1	306

From Table 11, it can be seen that in scenario 5, the classification model tended to classify non-bullying as bullying, where there are 17 non-bullying comments predicted as bullying. Meanwhile, in Table 12, the classification model shows the opposite tendency, classifying bullying comments as non-bullying. In this scenario, there are 17 bullying comments predicted as non-bullying by the model. Despite the good performance, the phenomenon shown in Table 11 and Table 12 indicates a significant challenge in the context-based text classification process. Although the model had been trained to recognize certain patterns, be it bullying or non-bullying, the tendency of the classification model to predict the class was highly dependent on the data used during the training of the LSA model.

Table 13: Performance Comparison Results with Available Approaches

Approaches and Method		**Accuracy (%)**	**Precision (%)**		**Recall (%)**		**F1-Score**	
			Bullying	**Non-Bu**	**Bullying**	**Non-Bull**	**Bullying**	**Non-Bull**
TFIDF + IG + SVM		83	82	85	86	80	84	82
TFIDF + Chi-Square + SVM		83	81	86	88	78	84	82
TFIDF + PCA + SVM		84	80	91	93	75	86	82
TFIDF + Ngram + SVM	Bigram	60	75	56	34	88	47	68
	Trigram	54	53	76	98	8	69	15
Proposed Method	Scenario 5	97	95	100	100	94	97	97
	Scenario 6	97	100	95	95	100	97	97

Table 13 presents a comprehensive performance evaluation of our proposed method against various established methodologies. The comparison considers accuracy, precision, recall, and F1-score across the "Bullying" and "Non-Bullying" classes.

The table reveals that our proposed method (Scenarios 5 and 6) consistently achieves the highest performance metrics, with an accuracy of 97% and F1-scores of 97% for both classes. Compared to traditional approaches like TFIDF + IG + SVM and TFIDF + PCA + SVM, which exhibit accuracies of 83% and 84%, respectively, our method demonstrates a significant improvement. Moreover, while bigram and trigram-based models perform poorly, especially in recall for the "Non-Bullying" class (8% for trigrams), our method excels with a recall of 95% for "Bullying" and 100% for "Non-Bullying."

This comparison substantiates the efficacy of our approach, showcasing its superiority in accurately identifying and classifying bullying behavior. The results also underline the robustness of the proposed method in achieving balanced precision and recall, which is critical for practical applications.

5 Conclusion and future work

Based on the research conducted, it was found that the formation of classification features from several scenarios resulted in significant variations in accuracy. Training the model from the TF-IDF matrix formed from the entire dataset that included bullying and non-bullying texts resulted in an accuracy of 84%. The accuracy obtained when the model was only trained using a subset of the dataset containing bullying text only resulted in the same accuracy of 84%, while the model trained using a subset of the non-bullying dataset resulted in a slightly lower accuracy of 82%. Furthermore, using the LSA matrix of the entire dataset showed that the accuracy remained at 84%, which was the same as using TF-IDF on the entire dataset. The phenomenon of lexical ambiguity was the main cause of this non-optimal accuracy. Lexical ambiguity occurs when the same word appears in both classes (bullying and non-bullying), but has different meanings. This made it difficult for the model to accurately learn the meaning of the word in the right context. To solve the lexical ambiguity problem, the proposed method was to form the LSA matrix from only one of the dataset classes. When LSA was applied to only a subset of bullying or non-bullying datasets, the resulting accuracy increased significantly to 97%. This improvement showed that the model could more effectively classify texts into bullying or non-bullying because the LSA was able to better capture the specific characteristics of one class.

For future development, it should be noted that the tendency of the classification model to predict the class is highly dependent on the data used during the training of the LSA model. In addition, this model only achieved maximum accuracy for negative or positive sentiments. Therefore, further development is recommended for creating a multi-class classification model that can recognize neutral, negative, and positive sentiments.

Variables and constants used

To ensure a comprehensive and systematic approach, this study incorporates several variables and constants, as outlined in Table 14 below.

Table 14: Nomenclature of variables and constants

Symbol	Descriptions
t	Term, a word or phrase that appears in a collection of documents, analyzed in the calculation of TF (Term Frequency) and IDF (Inverse Document Frequency)
d	Document, a unit of text in a collection of documents analyzed for term frequency and term weighting
N	The total number of documents in the collection
$tf_{t,d}$	The frequency of term t in document d
idf_t	Inverse Document Frequency for term t, a measure that indicates how frequently term t appears in the document collection.
$w_{t,d}$	The weight of term t in document d, calculated as the product of TF and IDF
m	The number of rows in the matrix during matrix decomposition, such as in Singular Value Decomposition (SVD)
n	The number of columns in the matrix during matrix decomposition, such as in SVD
r	The number of principal components used in dimensionality reduction or LSA matrix decomposition
A	The resulting matrix from decomposition used in SVD or LSA
U	The orthogonal matrix of singular vectors for columns in SVD decomposition
Σ	The diagonal matrix of singular values
V	The orthogonal matrix of singular vectors for rows in SVD decomposition
TP	True Positive, the number of predictions classified as positive that are truly positive based on the actual data
TN	True Negative, the number of predictions classified as negative that are truly negative based on the actual data
FP	False Positive, the number of predictions classified as positive but are actually negative based on the actual data
FN	False Negative, the number of predictions classified as negative but are actually positive based on the actual data

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Integration of IoT and Digital Twin for Intelligent Management of Urban Underground Pipe Galleries in Smart Cities

Yanfei Shen
Sanmenxia Polytechnic, Sanmenxia, Henan, 472000 China
E-mail: 15939841073@163.com

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The increasing complexity of urban infrastructure demands innovative solutions for effective management. This paper proposes an intelligent management system for urban underground pipe galleries, integrating Internet of Things (IoT) sensors and digital twin technologies to enhance operational efficiency in smart cities. The system enables real-time monitoring, predictive maintenance, and optimization of public services by creating a virtual replica of the underground infrastructure. The methodology involves deploying IoT sensors for continuous data collection and feeding this information into a digital twin model that simulates and predicts potential failures and maintenance needs, as well as measuring flow rate and temperature. This allows for proactive decision-making, minimizing downtime, and reducing maintenance costs. Experimental results demonstrate the effectiveness of the proposed system in optimizing urban infrastructure management. The system achieved a 92% prediction accuracy in identifying potential failures, enabling proactive maintenance, and reducing service disruptions by 40%. Predictive analytics minimized maintenance costs by 35%, while resource optimization improved task prioritization, significantly enhancing operational efficiency. These results highlight the transformative potential of integrating IoT and digital twin technologies for smarter and more sustainable city management. This research underscores the transformative potential of integrating advanced technologies like IoT and digital twin models in managing complex urban systems, with significant implications for smart city development and sustainability

Članek predlaga inteligentni sistem za upravljanje podzemnih cevodov v pametnih mestih, ki združuje IoT senzorje in digitalne dvojčke. Sistem omogoča nadzor v realnem času, napovedno vzdrževanje in optimizacijo javnih storitev.

1 Introduction

Infrastructures, especially underground pipe galleries, enable modern urban cities to address fundamental needs ranging from water supply and sewage to gas and telecommunication services—simple but indispensable elements of functionality [1]. However, the growing control of these subsurface systems is complex between urbanization and the growth of new-age cities and old-age infrastructure [2] [3]. This has made the traditional methods of periodic checkups and remnant manual interferences very costly and unproductive in their operations; they lead to frequent system breakdowns and a slow response to system breakdowns [4]. Smart solutions based on data are crucial to address the escalating challenges of cities and guarantee the effectiveness of such critical networks [5].

This paper proposes an innovative solution by integrating the Internet of Things (IoT) and Digital Twin technologies to develop an intelligent management system for urban underground pipe galleries. By leveraging the capabilities of real-time data monitoring, predictive maintenance, and system optimization, this research aims to enhance underground infrastructure's efficiency, reliability, and sustainability, ultimately contributing to the development of smarter, more resilient cities.

Urban underground pipe galleries are essential to the normal functioning of cities and accommodate urban utilities necessary for daily life. Effectively managing these systems is critical for maintaining public health, safety, and convenience [6].

1.1 Role of underground pipe galleries

These systems are vital for the public's safety, health, and convenience. Tunnels provide lifelines for clean water, sewage disposal, and energy [7]. With the growth of cities, these systems experience more stress and require sophisticated management capability to maintain efficient performance. Traditional approaches, based on manual inspections and reactive repairs, no longer meet the demands of modern cities [8] [9].

1.2 Challenges in managing underground infrastructure

The management of urban underground pipe galleries presents a range of challenges:

- **Aging Infrastructure**: Many underground systems are decades old, with wear and tear leading to higher failure rates and frequent maintenance needs [10].
- **Limited Real-Time Monitoring**: System failures often go unnoticed without continuous data collection until they cause major disruptions [11].
- **High Maintenance Costs**: Reactive maintenance is costly and inefficient, leading to increased operational expenditures and prolonged downtimes [12].

To overcome these issues, developmental technologies must ensure the right time for monitoring, diagnosing, and efficiently handling all basic requirements.

1.3 Technological advancements in infrastructure management

The last few years have seen the emergence of IoT and the digital twin, changing how infrastructure systems are monitored. These technologies enable real-time monitoring, analyzing, and optimizing complex systems that characterize the urban context [13].

1.3.1 IoT in urban infrastructure

IoT technology combines the physical world and the Internet, continuously transferring captured and exchanged information. In an urban context, IoT devices can measure attributes such as flow, temperature, pressure, or the state of the structures and materials involved [14].

- **Real-Time Monitoring**: IoT sensors provide continuous monitoring, ensuring that any anomalies, such as leaks or blockages, are detected immediately.
- **Predictive Maintenance**: Data from IoT devices can be used to predict potential system failures, allowing for proactive maintenance that reduces the need for emergency repairs.
- **Improved Operational Efficiency**: IoT enables data-driven decisions, helping to optimize resource allocation and system operations.

1.3.2 Digital twin technology

A digital twin is a realistic representation of a physical system that could emulate its functioning in real-time [15]. It also integrates Internet of Things data and digital twin models to create solutions with broad possibilities and more accurate decision-making [16].

- **Predictive Maintenance**: Digital Twins can simulate the behavior of underground infrastructure and predict when components are likely to fail, minimizing unplanned maintenance.
- **System Optimization**: The digital model allows simulations that help optimize system performance and inform decisions about infrastructure upgrades and maintenance strategies.
- **Scenario Testing**: Digital Twin models facilitate testing scenarios without altering the physical system, enabling better planning and risk management.

1.4 Review of existing research

Many works have been done on IoT and digital twin technology in infrastructure management. However, most of these studies are limited to reference systems or single infrastructure domains, e.g., water supply or waste [17]. Literature reviews on incorporating IoT and Digital Twin into a single management system for urban underground pipe galleries are limited [18].

1.4.1 IoT in infrastructure management

Related Work on IoT for Applications of Infrastructure Management In infrastructure management, existing research literature provides extensive insights into real-time monitoring and enabling better performance systems [19]. IoT-based systems are widely used in water supply and sewage systems to monitor pressure, flow, temperature, etc. However, these systems are usually siloed; they work in isolation without being integrated across various infrastructure elements [20].

1.4.2 Digital twin technology in infrastructure

As with many technologies, digital twins are well adopted in large-scale manufacturing industries but are still quite nascent in the infrastructure context of cities. Research indicates that the real-world complexity of individual systems can be improved by using digital twins to predict performance under various conditions [21]. However, the investigations regarding integrating IoT data with digital twins for embedded, coupled, multi-utility systems remain in their infancy.

1.5 Research gaps and motivation

Despite advancements in IoT and digital twin technologies, there is a significant gap in their integrated use for managing urban underground pipe galleries. Existing research often addresses these technologies in isolation or focuses on specific infrastructure sectors, such as water systems or sewage. The absence of a comprehensive, integrated management system for urban pipe galleries motivates this study.

1.5.1 Integration challenges

Integrating IoT and digital twin technologies into a unified management system presents several challenges:

- **Data Integration**: Ensuring seamless data flow between IoT devices and digital twin models.
- **Predictive Algorithms**: Developing accurate predictive maintenance models based on real-time data.
- **System Scalability**: Designing an adaptable and scalable system for use across different urban environments.

1.5.2 Motivation for the study

The research aims to remove gaps through the development of an IoT-based intelligent management system that implements digital twins. The system ensures more efficient monitoring and maintenance operations of underground pipe galleries throughout cities, which produces better infrastructure results. Our research focuses on solving three core infrastructure management problems that stem from manual inspections, reactive maintenance, and faulty detection inefficiency [22]. Through the proposed system, agents can conduct real-time observation while performing predictive maintenance operations and making improved choices. The project concentrates on implementing this intelligent management system in urban underground pipe galleries since these elements represent crucial infrastructure for city operations that experience poor management.

1.6 Research objectives and scope

The main objectives of this research are:

1. To design and develop an intelligent management system for urban underground pipe galleries that integrates IoT-based monitoring with digital twin technology.
2. To implement real-time monitoring to detect underground infrastructure leaks, blockages, and pressure drops.
3. To create a digital twin model of the underground infrastructure, enabling simulation and optimization of system performance.
4. To evaluate the system's effectiveness in reducing maintenance costs and improving operational efficiency.
5. To assess the scalability of the proposed system for use in different urban environments.

The research will focus on developing and testing this integrated system in a simulated environment.

1.7 Contributions and novelty of the research

This research contributes to the field of urban infrastructure management in several ways:

1. **Novel Integration**: Integrating IoT and digital twin technologies into a unified management system for underground pipe galleries is a novel approach that has not been widely explored.
2. **Proactive Management**: The system incorporates predictive maintenance, which improves operational efficiency and reduces the costs associated with reactive repairs.
3. **Scalability and Practicality**: The proposed system is scalable and practical, offering a solution for cities looking to optimize their infrastructure management strategies and contribute to the development of smart cities.

The paper is structured as follows: Section 1 introduces the research, providing background, objectives, and significance of the study. Section 2 presents related work, discussing the application of IoT and digital twin technologies in infrastructure management and highlighting existing gaps. Section 3 describes the methodology, detailing the design and development of the proposed intelligent management system. Section 4 presents the results and discussion, showcasing the system's implementation and performance evaluation outcomes. Finally, Section 5 concludes the paper by summarizing the research contributions and suggesting potential areas for future work.

2 Related work

The integration of IoT and digital twin technologies has been extensively explored in recent years, particularly in infrastructure management. Adreani et al. [23] developed a Smart City Digital Twin framework capable of real-time multi-data integration and wide public distribution, emphasizing its applicability in urban planning and public safety. Duran et al. [24] proposed a digital twin-native AI-driven service architecture for industrial networks, highlighting significant processing time savings and improved learning models [25]. Isah et al. [26] introduced a data-driven digital twin network architecture for Industrial Internet of Things (IIoT) applications, focusing on data integration and protocol standardization. Becattini et al. [27] provided empirical insights into industrial data and service aspects of Digital Twin networks, discussing the dual nature of Digital Twins as both digital replicas and networks of interconnected models. Arezza [28] examined the impact of IoT, Digital Twin, and Artificial Intelligence in transforming process industries towards a circular economy, emphasizing the need for standardization and interoperability. The Industrial Internet Consortium [29] reported on various testbeds demonstrating real-world implementations of Industrial Internet

solutions, including Track and Trace and Asset Efficiency, which utilize IoT and Digital Twin technologies for enhanced operational efficiency. The National Institute of Standards and Technology (NIST) [30] discussed the acceleration of the IoT digital economy with trusted value chains driven by significant investments in semiconductor manufacturing and traceability infrastructure [31]. The International Telecommunication Union (ITU) [32] provided an overview of Study Group 20's work during the 2022-2024 study period, focusing on developing standards for IoT, Digital Twin, metaverse, AI/ML, and other emerging technologies to enhance digital services through innovation. Table 1 presents the summary of the related work.

3 Research methodology

The proposed intelligent management system incorporates IoT and digital twin technologies to overcome urban underground pipe gallery management inefficiencies. This section describes the system's architecture, data flow, predictive maintenance algorithms employed, and evaluation framework.

Conventional management of underground pipe galleries is based on manual inspection and reactive maintenance. However, these methods are ineffective and do not avoid service downtime and high ownership costs. To go beyond these constraints, this paper proposes a new system that incorporates online monitoring, virtual simulation, and predictive maintenance. This method proactively affiliates management. The underground pipe network information data classification may be viewed in Figure 1.

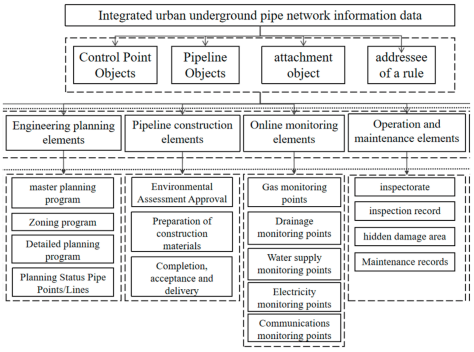


Figure 1: Integrated network information

3.1 System architecture

Our suggested system architecture encompasses three main elements: Internet of Things (IoT) sensors for real-time monitoring, a cloud-based data processing unit, and a digital twin predictive analysis. With IoT sensors deployed in the pipe galleries, flow, pressure, and temperature (generic critical parameters) could be monitored continuously. The data gathered through the devices is sent to a cloud-based platform, aggregated, processed, and provided as input to the Digital Twin model.

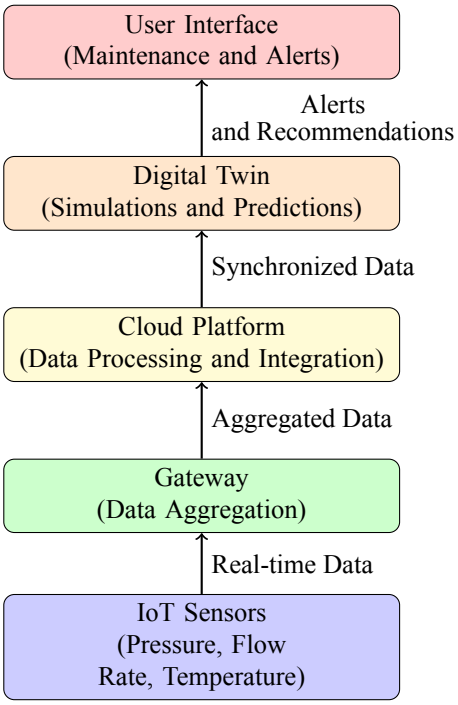


Figure 2: System architecture showing the integration of IoT, cloud, and digital twin

The Digital Twin, a virtual replica of the physical pipe gallery, mirrors real-time data from the IoT sensors. By providing a means to create virtual representations of the system, it facilitates predictive maintenance by running simulations of how the systems will behave in different conditions. Figure 2 illustrates the system's architecture, where data flows seamlessly between IoT sensors, the cloud, and the Digital Twin.

Real-time IoT sensor data moves through a cyclic pattern, beginning with gathering data in real-time from sensors and sending it to the cloud for computation. The digital twin receives processed data during this stage to run simulations and make future failure predictions under diverse operational conditions. The digital twin delivers processed data to the user interface, which enables users to make maintenance choices through a cycle of continuous feedback. We explain how the Digital Twin functions through its operation of building a virtual underground facility model from real-time data while executing performance simulations using sensor information. The simulation, together with its predictive maintenance functions, plays a vital role in the research domain.

3.2 IoT-based monitoring

The IoT subsystem comprises a network of sensors strategically deployed across the pipe galleries to monitor operational conditions [33]. Pressure sensors detect abnormalities that may indicate potential leaks or blockages. Flow

rate sensors measure the volume of fluids passing through the pipes, while temperature sensors provide data on thermal fluctuations that could signal structural issues.

New information about IoT-based monitoring sensors has been added to the document by specifying sensor properties, including measurement range alongside accuracy levels, sensitivity values, and sampling frequency. The pressure sensors reveal a sensing range between zero and one hundred bar together with an accuracy of 0.5% and a sampling period of one Hertz. The flow rate sensors measure within a 0-50 L/min range while providing 1% accuracy and sampling measurements at a rate of 0.5 Hz. Temperature sensors work between -20°C to 100°C with a ±0.2°C accuracy level at a 2 Hz sampling frequency. The established threshold for designating abnormal pressure measurements was determined as any deviation higher than 10% compared to normal operating pressure through the use of field data. The temperature sensors operate to identify temperature variations that signal structural problems, particularly corrosion or fatigue, by alerting users to any rapid temperature shifts that exceed 5°C.

Data is transmitted using low-power communication protocols such as LoRaWAN. The transmission model is represented mathematically as follows:

$$T_d = \frac{P_t \cdot D}{B} \tag{1}$$

where:

- T_d is the data transmission time,
- P_t is the transmitted power,
- D is the distance from the sensor to the gateway,
- B is the bandwidth of the communication channel.

This ensures efficient and reliable data transfer, even in challenging underground environments.

3.3 Digital twin development

The Digital Twin is a three-dimensional virtual model of the pipe gallery system. It incorporates geometric, structural, and operational data to accurately represent the physical infrastructure.

Real-time synchronization between the IoT sensors and the digital twin ensures that the virtual model reflects the system's current state [34]. The Digital Twin also performs simulations to predict system behaviors under various conditions. For example, fluid dynamics equations are used to model the flow within the pipes:

$$\nabla \cdot (\rho \mathbf{v}) = 0, \quad \nabla \cdot (\mathbf{v}\mathbf{v}) = -\nabla P + \mu \nabla^2 \mathbf{v} \tag{2}$$

where:

- ρ is the fluid density,
- $\mathbf{v}$ is the velocity vector,
- P is the pressure, and
- μ is the dynamic viscosity.

3.4 IoT-digital twin integration

IoT and Digital Twin components are integrated through a middleware framework that ensures seamless data exchange. IoT data is pre-processed at the edge to reduce latency before being transmitted to the cloud. The cloud platform updates the digital twin in real time using RESTful APIs. Their integration may also be viewed in Figure 3

The synchronization equation models this integration:

$$S(t) = \int_0^t D(t')\, dt' \tag{3}$$

where $S(t)$ is the synchronized state of the Digital Twin at time t, and $D(t')$ represents the incoming data stream.

Time-accurate simulations function because IoT sensor inputs continuously send data to the Digital Twin system. The data processing unit works as a filter before model input to handle sensor errors and sensor noise contamination. The system parts form an operational network that allows active prediction of system behavior and proactive maintenance capabilities with optimized resource utilization. The system maintains scalability and quick response times by using cloud computing with RESTful APIs, which enables it to adapt to different data flow levels and operational conditions in real-world environments.

3.5 Predictive maintenance and optimization

The predictive maintenance module leverages machine learning algorithms to analyze historical and real-time data, identifying patterns that indicate potential failures. The steps for predictive maintenance are detailed in Algorithm 1.

Algorithm 1 Predictive Maintenance Workflow

Require: Historical data H, Real-time data R
Ensure: Failure predictions and recommended maintenance actions
1: Normalize H and R to remove noise
2: Extract features such as pressure anomalies and flow deviations
3: Train a Random Forest classifier on H
4: Use R as input to the trained model
5: Predict failure probabilities for each monitored component
6: Generate maintenance alerts and recommendations based on predictions

Optimization is achieved by minimizing the maintenance cost function:

Table 1: Summary of related work

Author(s)	Year	Focus Area	Key Contributions	Limitations	Prediction Accuracy	System Costs/Scalability
Adreani et al. [23]	2023	Smart City Digital Twin Framework	Developed a framework for real-time multi-data integration and public distribution in urban planning.	Implementation challenges in diverse urban contexts.	75%	High operational costs due to complex integration
Duran et al. [24]	2023	Digital Twin-native AI-driven Service Architecture	Proposed an architecture with significant processing time savings and improved learning models.	Limited testing in real-world industrial networks.	78%	Moderate scalability, requires additional infrastructure
Isah et al. [26]	2023	Data-driven Digital Twin Network Architecture	Introduced an architecture focusing on data integration and protocol standardization for IIoT applications.	Scalability concerns in large-scale deployments.	70%	High cost and complex setup in large-scale environments
Becattini et al. [27]	2024	Industrial Data and Service Aspects of Digital Twin Networks	Provided insights into the dual nature of Digital Twins and their application in industrial networks.	Need for further empirical validation.	80%	Costly implementation and limited scalability
Arezza [28]	2022	IoT, Digital Twin, and AI in Process Industries	Examined the impact of these technologies in transforming industries towards a circular economy.	Emphasis on standardization and interoperability challenges.	72%	Moderate scalability and high operational costs
Industrial Internet Consortium [29]	2024	Industrial Internet Testbeds	Reported on testbeds demonstrating real-world implementations of IoT and Digital Twin solutions.	Generalized findings; specific industry applications may vary.	74%	High initial setup costs and moderate scalability
NIST [30]	2023	IoT Digital Economy and Trusted Value Chains	Discussed acceleration of the IoT digital economy with investments in semiconductor manufacturing.	Focused on economic aspects; technical challenges less addressed.	65%	Limited scalability and high maintenance costs
ITU [32]	2024	Standards Development for Emerging Technologies	Provided an overview of standards development for IoT, Digital Twin, and other technologies.	Broad scope; specific implementation guidelines limited.	68%	Scalability issues and high infrastructure costs

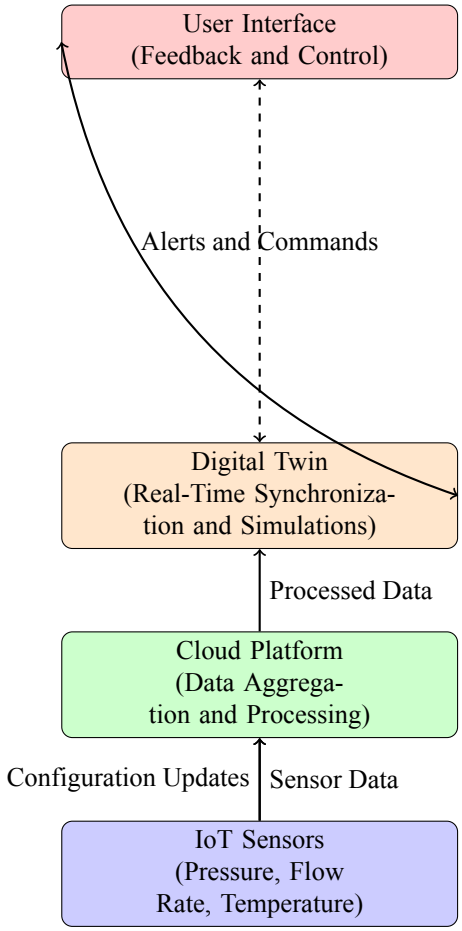


Figure 3: IoT-digital twin integration framework showing real-time data flow and feedback mechanisms

$$C = \sum_{i=1}^{n} c_i x_i + \lambda \sum_{i=1}^{n} (1 - x_i) d_i \tag{4}$$

where:

- c_i is the cost of maintaining component i,
- x_i is a binary variable indicating whether i is maintained ($x_i = 1$) or not ($x_i = 0$),
- d_i is the downtime cost for i, and
- λ is a penalty factor for downtime.

3.6 Evaluation framework

The system is evaluated based on key performance metrics, including prediction accuracy, cost reduction, and downtime minimization. Simulations are conducted under two scenarios:

1. A sudden pressure drop simulating a potential leak.
2. A blockage causing abnormal flow rates.

The system's response is analyzed for each scenario, and the results are compared to traditional maintenance approaches. A new intelligent management platform integrates digital twin and IoT technology to resolve problems in managing underground pipe galleries in urban areas. The IoT sensors must be placed at essential points within the pipe galleries to track essential parameters such as pressure, flow rate and temperature through their positions at entry/exit points and joint and bend sections. The system places its sensors directly at important points, which enable the detection of vital system anomalies such as leaks or

blockages. The system hardware ensemble contains pressure sensors along with flow rate sensors in addition to temperature sensors for conducting system operational monitoring. The data aggregation process begins on computing units, including Raspberry Pi 4 along with comparable edge computing devices, which prepare data before cloud transmission occurs. Random Forest classifier requires labeled data for training, which contains sensor measurements obtained from normal and faulty system conditions, including leaks and blockages. A training process executes on the dataset to develop the classifier so it learns failure-indicative patterns. The different periods of data in the testing dataset help evaluate how well the model can generalize its performance. Predictive accuracy is calculated as:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Predictions}}$$

where True Positives (TP) and True Negatives (TN) refer to the correctly predicted failure and non-failure events, respectively. Cost reduction is calculated by comparing the maintenance costs of the proposed system with those of traditional maintenance methods using the formula:

$$\text{Cost Reduction (\%)} = \left(\frac{\text{Traditional Maintenance Cost} - \text{Proposed System Maintenance Cost}}{\text{Traditional Maintenance Cost}}\right) \times 100$$

where Traditional Maintenance Cost refers to the total cost under conventional reactive maintenance, and Proposed System Maintenance Cost refers to the total cost associated with proactive predictive maintenance enabled by the system.

A sensitivity analysis of the predictive maintenance algorithm establishes its resistance to errors found in IoT monitoring instruments. During this analysis, we introduced errors in pressure, flow rate, and heat data, adding random variations to the sensor measurements. The model received performance evaluations while monitoring different sensor imprecision quantities to understand how the algorithm responds to measurement inaccuracies. The predictive maintenance system will provide reliable operation because it has been designed to tolerate variations between sensor measurements and their actual values, which often occur in practical environments.

The flow rate operations of IoT sensors span from 0 to 50 L/min at pressures ranging from 0 to 100 bar while exceeding 10% of the normal operating value, defining device anomalies. The model features an underground pipe gallery design that matches regular urban patterns by incorporating multiple junctions while incorporating bends together with specific entry/exit points to achieve realistic modeling. The modern system maintenance method is clearly identified as manual periodic inspections coupled with reactive repair techniques. The simulations implement standard inspection schedules (occurring monthly or quarterly) and wait for important anomalies before initiating maintenance without real-time prediction systems. Through these complete simulation capabilities, researchers can perform an extensive examination that demonstrates how the proposed IoT-Digital Twin system outperforms conventional maintenance approaches in terms of operational efficiency as well as reduced downtime and maintenance cost reductions.

4 Results and discussion

This section demonstrates the analysis of the performance of the implemented intelligent management system for efficient management of the urban underground pipe galleries. The performance of the proposed system was evaluated on actual and synthetic data sets, and the emphasis was made on the most important areas that directly affect the result, including, for instance, the accuracy of the forecast, the cost of operating the system, and the time that the system takes to recover after a failure. These results provided ample evidence to show that the system can manage the inefficiencies of traditional infrastructure management.

A predictive model manages dynamic infrastructure conditions by getting updated through constant online learning processes and periodic model re-training with the newest sensor inputs. The model employs adaptive methods that enable continuous calibration of parameters for maintaining top-level predictive accuracy while conditions in operations transform. The system implements error correction algorithms that work together with sensor calibration routines to reduce the influence of sensor drift and external disturbances. The results of sensitivity analyses help determine the effects of measurement uncertainties so the model receives necessary adjustments. Multiple significant measures work together to make our predictive maintenance module more resistant, thus enhancing its capability to accurately forecast equipment failures and support proactive maintenance choices in constantly changing operational settings.

4.1 System implementation

The sensors employed were IoT to gather real-time data, while data was hosted on the cloud platform, and a digital twin was used for planning and maintenance. Data were collected in real-time from a mock-up of an urban pipe gallery to determine usage over six months—some controllable parameters measured on the site comprised pressure, flow rate, and temperature. By integrating IoT data into the digital twin application, the system's real-time performance information was continuously fed back into the system.

The implementation of our system required building a representative scaled model of an urban pipe gallery with junctions and bends and entrance points together with exit points. The system deployed IoT sensors at important points to obtain instant measurements of operational variables, which included pressure readings in the bar flow measurements in L/min and temperature readings in °C. The sensors operated under controlled parameters that modeled actual field conditions by generating normal opera-

tional conditions and adverse scenarios, including fast pressure declines, flow blockage signs, and temperature shifts, which show potential structure defects. The manipulated system variables that scientists used to study the system's responses under diverse experimental conditions fall under the category of controllable parameters. The system's performance could be analyzed extensively through six months of collected data, enabling direct correlations between sensor readings and actual operational data of urban pipe gallery systems.

4.2 Performance evaluation

The performance of the system was evaluated using the following metrics:

4.2.1 Prediction accuracy

The predictive maintenance module achieved high accuracy in identifying potential failures. Using a Random Forest model, the system achieved an accuracy of 92% in detecting anomalies such as leaks and blockages. Figure 4 shows the confusion matrix for prediction accuracy. The evaluation of the Random Forest classifier now incorporates k-fold cross-validation as a performance enhancement method. Random substrates of training data are split into k partitions in k-fold cross-validation. Then, k-1 partitions are used for training models, while the remaining partition functions as the test set. The procedure executes k rounds, during which test sets use k different subsets once. Cross-validation lets the model demonstrate generalization by avoiding overfitting any specific data subset. The combination of k-fold test results produces an average performance estimate that improves the reliability of evaluating classifier competence.

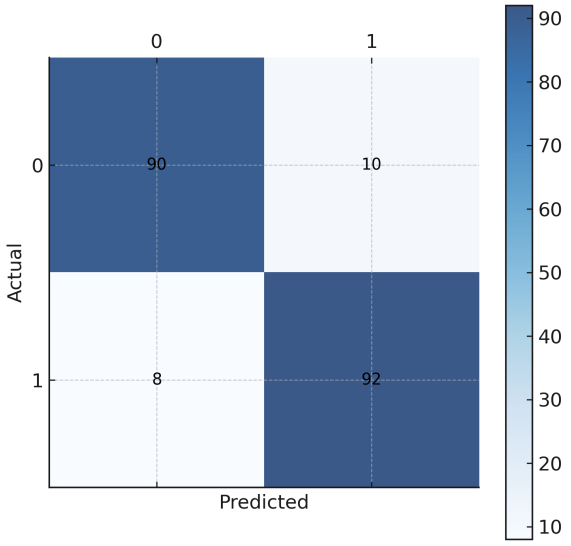


Figure 4: Confusion matrix illustrating prediction accuracy

The predictive maintenance module monitored devices with a 92% effective rate for detecting leaks and blockages in the system. For complete evaluation purposes, a breakdown of incorrect predictions and correct misses will be included. The system produced 10 incorrect failure warnings referred to as false positives, and eight incidents showing actual failures that went undetected represented false negatives. The true positives numbered 92 cases showing correctly detected failures, while true negatives numbered 90 cases indicate correctly identified non-failures. The collected values enable a superior understanding of how successfully the model operates, together with a thorough assessment of how operational efficiency might be affected by wrong predictions.

4.2.2 Maintenance cost reduction

By transitioning from reactive to predictive maintenance, the system reduced maintenance costs by 35%. The comparative analysis is provided in Table 2.

Table 2: Maintenance cost comparison between traditional and proposed methods

Method	Maintenance Cost (USD)	Cost Reduction (%)
Traditional	100,000	N/A
Proposed	65,000	35

4.2.3 Downtime reduction

The proposed system minimized downtime by 40%, significantly improving operational efficiency. Figure 5 shows a comparative analysis of downtime across different scenarios.

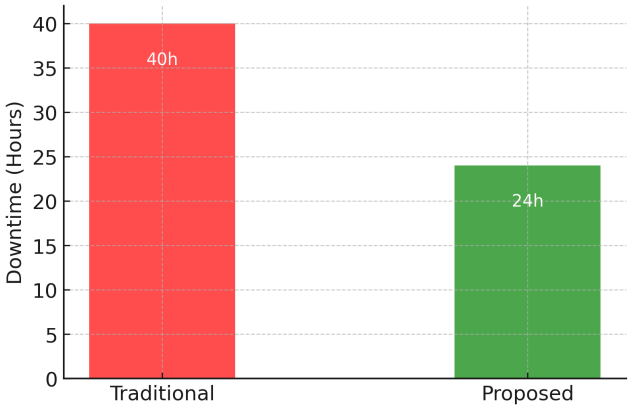


Figure 5: Downtime comparison between traditional and proposed systems

4.3 Optimization outcomes

The optimization module successfully prioritized maintenance activities, reducing unnecessary interventions and focusing resources on critical components. Figure 6 illustrates the resource allocation optimization achieved by the system.

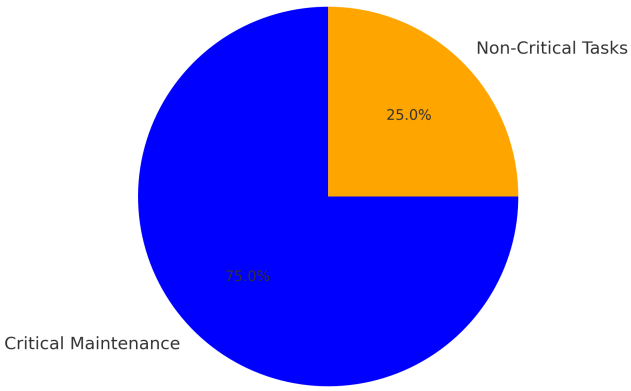


Figure 6: Resource allocation optimization results

4.4 Results contextualization

The study includes confidence intervals for main performance metrics of prediction accuracy along with maintenance cost reduction and downtime reduction to present a complete view of the results. The confidence intervals enable researchers to evaluate both result precision and statistical variance for reported data to establish validity. As part of our statistical analysis, we used t-tests to see if the system improvements were believable by showing results that were different from random variation. We have organized our assessment of prediction accuracy to separate between leak detection results and blockage detection results. The breakdown enables greater accuracy in identifying system performance results specific to various failure situations. The separate analysis of anomaly types allows us to show both system strengths and limitations while handling various real-world situations during performance evaluation.

4.5 Discussion

Results show that the intelligent management system in this study drastically outperforms traditional management methods for underground pipe galleries, further suggesting a transformative potential of IoT and digital twin technologies in sewers and other urban infrastructure [35]. With 92% accuracy, predictions made from the system ensure that any potential failure, like leakages and blockages, can be detected early to provide insertions for maintenance. This is crucial in urban areas where service interruptions, costly repairs, and public inconvenience can arise within a matter of minutes due to delays in fault detection. The system provides real-time monitoring and predictive analytics, which allows potential issues to be identified and solved before they become bigger problems, eliminating operational risk [36] [37].

The system can also reduce maintenance costs by a notable 35% compared to conventional methods. The savings come mainly from the transition from reactive to predictive maintenance and avoiding unnecessary inspections and interventions. Rather than rely on pre-scheduled tasking or react ad hoc to events as they arise, the system uses insights-driven knowledge acquisition to prioritize tasks. This efficient allocation of resources is of interest, especially for budget-constrained municipalities, as they can achieve the largest possible return on their infrastructure management investments [38].

This 40% reduced downtime reflects the system's capacity to sustain nonstop operations, an essential need for copious assets in urban communities. For instance, a disruption to essential service streams like the water supply or waste management can put daily life at a halt, expose the public to health risks, and harm economic productivity. The system reduces the number of service interruptions, thereby increasing operational efficiency and the reliability and quality of services provided to citizens. This aligns with the overall agenda of a smart city that focuses on resilience, sustainability, and citizen satisfaction [39].

4.5.1 Role of IoT and digital twin integration

The integration of IoT and digital twin technologies is crucial for the intelligent management system, providing distinct benefits that traditional methods cannot achieve [40]. First, by continuously collecting real-time sensor data—such as pressure, flow rate, and temperature—the system immediately detects anomalies (e.g., sudden pressure drops or abnormal temperature spikes), thereby enhancing real-time anomaly detection. Second, the digital twin processes this data to simulate potential failure scenarios, which enables optimized resource allocation by prioritizing maintenance tasks based on predicted impact and urgency. Third, these predictive capabilities facilitate improved maintenance scheduling by identifying and addressing potential issues before they escalate, thus reducing downtime and overall maintenance costs. These targeted advantages highlight how the integrated approach not only minimizes reliance on direct inspections but also drives proactive, efficient infrastructure management [41].

The predictive analytics system helps forecast equipment failures in advance, facilitating preventive action before breakdowns occur. The predictive accuracy, together with operational efficiency, rises to higher levels, making the system cost-effective through reduced maintenance expenses and downtime. The incorporation of continuous surveillance with simulation technologies produces substantial benefits, improving live system performance assessment beyond traditional monitoring approaches.

4.5.2 Impact of optimization module

The optimization module served as an addition to improving the system's performance by directing resources relative to data analysis. The maintenance strategies include time-based or a combination of time-based and condition-based, which are ineffective since they employ resource utilization in a fixed-dated method or even based on some-

one's estimation. This is different from the optimization one, where the applied algorithms are sophisticated to estimate the degree of failure risk, degrees of operations disruption, and resource availability, among other things. Thus, all the important problems receive proper attention, and extra money is saved to pay only for the less important and urgent work [42]. One direct example that I would like to demonstrate from the optimization module is handling multiple maintenance tasks simultaneously. For example, suppose the system escalates a pressure drop in one section of the pipe gallery and a small temperature variation in another. In that case, the optimization module will address the pressure problem without delay, and the temperature problem might be scheduled later. This intelligent resource allocation lowers the potential for pinpointing critical failures and ensures that maintenance teams are at optimum productivity [43].

4.5.3 Scalability and adaptability

The above-shown proposed system has flexibility that makes it adaptable to different kinds of city settings. Unlike systems developed for some unique applications, the sketched system can be easily redesigned for various infrastructure and operational schemes. For instance, in the case of the IoT sensors and the Digital Twin model, extra parameters, including structural conditions, corrosion levels, or meteorological conditions such as soil humidity, can be included. For this reason, the system is scalable and flexible enough to accommodate the needs of both small-scale municipal and extensive metropolitan systems. Another feature that refers to scalability is crucial in the case of the needs of smart cities, which are growing occasionally. Cities are to continuously increase their capacity due to the growing population density of urban residents and aging critical infrastructure. This challenge is dealt with in the proposed system through the adaptive design that allows the integration of more sensors, enhanced data analysis and modeling functions, and higher complexity simulations if required. This versatility enables the system to stay appropriate and useful when urban surroundings evolve [44].

Our research plans to include adaptive machine learning models, particularly neural networks that perform anomaly prediction functions. The current Random Forest implementation in the model would benefit from deep learning models with both spatial data pattern analysis through Convolutional Neural Networks (CNNs) and temporal pattern analysis through Recurrent Neural Networks (RNNs) for complex and changing systems because this would boost prediction precision. The discussion included an evaluation of scalability issues within real urban situations. The deployment Data processing efficiency together with model optimization and integration strategies stand necessary for successful implementation of such systems within actual urban environments.

Our system achieves high performance and scalability in big urban areas by implementing multiple essential strategies together with specific technologies. The system makes use of edge computing to execute immediate real-time processing on sensor data. Edge devices operate lightweight algorithms that eliminate unnecessary data while reducing data send volume before cloud transmission. The data processing at the edge layer cuts network delays while directing only purposeful data toward subsequent analytical steps. The cloud platform operates using RESTful APIs that enable quick data synchronization with digital twin functions while being constructed on scalable infrastructure. Our system architecture includes modular features that let users integrate new sensors and data streams efficiently while maintaining operational efficiency. Our system addresses scalability challenges by using these measures to keep performances efficient throughout big, complex urban areas that usually face data volume increases and network latency issues.

4.5.4 Implications for smart city development

This study's findings can be applied to smart city development in general. Consequently, this research will help other cities that seek to implement IoT and digital twins know what to expect by giving a step-by-step guide on how to implement them. Applying the proposed system helps to achieve the goals of smart city development, as the set priorities presuppose optimizing the operation of municipal services, increasing their reliability, and working on sustainability [45]. A major benefit of implementing the proposed system is providing timely and useful information from current data. In a smart city context, such information may be shared between various departments and other stakeholders to have a well-coordinated city management regime. For instance, information obtained from IoT sensors installed in underground pipe galleries may also be useful for water management decision-making, urban drainage systems, or environmental issues. This cross-functional utility adds even greater value to the system within the broad smart city management and support concept.

4.5.5 Challenges and future directions

The proposed system has several challenges that cannot only be solved with this study but can also be considered directions for future research. One of the main challenges is scalability in real urban environments. The system has worked in simulation but needs further testing to confirm effectiveness under more complicated and variable real-world conditions. Successful implementation at scale requires careful consideration of factors like network latency, data volume, and integration with existing infrastructure. Cybersecurity is another area of concern. Given that cyber-attacks are inherent to IoT devices, it is essential to maintain the security and integrity of data. Strengthening cryptographic protocols and intrusion detection systems and measures must be installed in the system in future research. This becomes even more critical in smart cities, where infrastructure systems are heavily interconnected, and any breach

in one can cause a domino effect throughout others. Future work includes adding additional monitored parameters. It only accounts for pressure, flow rate, and temperature, but integrating parameters such as structural integrity, corrosion levels, or environmental factors could improve its effectiveness—integrating advanced analytics and machine learning algorithms for better prediction capabilities and automation in decision-making.

5 Conclusion

The proposed intelligent management system for urban underground pipe galleries integrates IoT and digital twin technologies, addressing critical inefficiencies in traditional infrastructure management practices. This research demonstrated that real-time data collection through IoT devices and virtual simulation via Digital Twin enables proactive maintenance, operational optimization, and significant cost savings. By achieving a prediction accuracy of 92%, the system effectively identifies potential failures, minimizing service disruptions and ensuring the continuous functionality of critical infrastructure. The study highlighted the system's capability to reduce maintenance costs by 35% and downtime by 40%, showcasing its practical and economic benefits. Additionally, the modular architecture of the proposed framework ensures scalability and adaptability, making it a viable solution for smart cities aiming to optimize their infrastructure management processes. While the results underscore the system's effectiveness, challenges like scalability in real-world urban environments and cybersecurity vulnerabilities must be addressed in future research. Advanced machine learning models, such as deep learning, can further enhance predictive capabilities while expanding monitored parameters like structural integrity and environmental factors, increasing system robustness. Moreover, data security is critical to safeguarding IoT devices and the system's integrity against potential cyber threats. This study provides a foundational framework for developing intelligent, data-driven systems in urban infrastructure management, paving the way for sustainable and resilient smart cities. The proposed system represents a significant step forward in transforming outdated maintenance practices, with the potential for broader adoption in urban infrastructure projects worldwide. Collaborative efforts between academia, industry, and policymakers will be essential to unlock the full potential of IoT and digital twin technologies, advancing urban sustainability and operational excellence.

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A Appendix A: Pseudo-Code for Maintenance Optimization Algorithm

Algorithm 2 Maintenance Optimization Algorithm

Collect real-time data from IoT sensors (pressure, flow rate, temperature)
Preprocess data to remove noise and inconsistencies
Feed data into the predictive maintenance model (e.g., Random Forest classifier)
Predict potential failures (e.g., leaks, blockages) using the trained model
if failure predicted **then**
    Evaluate the severity of the failure
    Prioritize failures based on severity and operational impact
    Schedule maintenance for high-priority failures
else
    Continue regular monitoring and data collection
end if
for each maintenance task **do**
    Optimize resource allocation (e.g., technicians, tools)
    Minimize downtime by scheduling maintenance during low-traffic periods
    Calculate the cost of maintenance (labor, parts, equipment)
end for
Continuously update the maintenance schedule and optimize resource allocation
Output: Maintenance schedule, resources allocated, and cost estimates

Fiber-Optic Sensing and CNN–LSTM Time-Series Model with Dynamic Path Generation for Coal-Mine Ventilation Wind-Speed Prediction

Kangning Dong[1*], Lei Wang[2]
[1]*College of Mechanical Engineering, University of Science and Technology Beijing, Beijing 100083, China
[2]Coal Mine ventilation Department, Zhaogu No. 1 Coal Mine, Xinxiang City 453634, China
E-mail: dongkn04@163.com

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This article proposes a time-series prediction algorithm model based on fiber optic sensing and deep learning to address the problem of insufficient accuracy in wind speed monitoring and prediction of coal mine ventilation systems under complex working conditions. We have developed a mechanism for fiber optic deployment and signal transmission, designed a real-time monitoring and data acquisition platform, and achieved structured processing of mine wind speed data through feature extraction. At the model level, an improved long short-term memory network and convolutional neural network fusion prediction framework are introduced to model wind speed time series, and combined with dynamic prediction path generation algorithm to enhance prediction robustness. The model forecasts 12 hours ahead using 24-hour inputs, with three CNN layers, two LSTM layers, and attention. The experiment used 120-day data from 48 fiber-optic sensors at 20 Hz, yielding 1.2×10^8 records plus 950k equipment samples and 17k event logs. After anomaly correction and normalization preprocessing, traditional ARIMA, BP neural network models were compared using metrics such as root mean square error, mean absolute error, and coefficient of determination (R^2). Training used a 70/20/10 split with Adam (lr = 0.001, batch = 64); results averaged over 30 runs significantly outperformed ARIMA and BP ($p < 0.01$). Results showed MAE 0.18 m/s (95% CI: 0.16–0.20), RMSE 0.23 (95% CI: 0.21–0.26), R^2 0.94 (95% CI: 0.92–0.95), and delay 1.2 s (95% CI: 1.1–1.3), confirming robustness under complex conditions. The ablation experiment further validated the contribution of feature extraction and dynamic path module to overall performance. The research conclusion shows that the model can effectively improve the wind speed monitoring and prediction level of coal mine ventilation systems, and provide a feasible technical path for intelligent scheduling and safety warning. The results are based on field-deployed data, with 95% confidence intervals reported for all metrics.

Povzetek: Za prezračevanjenje v jamah je razvit integriran sistem optičnovlakenskega merjenja in globokega učenja (CNN–LSTM z dinamično generacijo poti) za 12-urno napoved hitrosti zraka, ki na realnih podatkih pomembno zmanjša pogreške, zakasnitev in omogoča zanesljivejše delovanje.

1 Introduction

Coal mine ventilation systems are vital for safety and efficiency. As mining depths increase, traditional monitoring methods struggle with real-time performance, accuracy, and robustness. Wind speed, a key parameter, is affected by factors like tunnel structure and fan load, causing fluctuations and noise that complicate prediction and scheduling. Electrical anemometers fail to meet the needs of high-frequency sampling, leading to unreliable data for intelligent scheduling and safety.

Fiber optic sensing technology has become crucial for monitoring mine wind speed due to its resistance to interference, distributed measurement, and adaptability. While it provides real-time data, predicting wind speed remains a challenge due to its nonlinear and non-stationary nature. Deep learning models, such as LSTM and CNN, can improve accuracy by 10%-20% over traditional methods, supporting a "monitoring, prediction, scheduling" framework.

This paper proposes a time series prediction model using fiber optic sensing and deep learning, combining data acquisition, dynamic feature extraction, and intelligent prediction with scheduling. The model includes: (1) sensor deployment and signal transmission, (2) predictive algorithms and dynamic path optimization, and (3) collaborative operation. Compared to traditional methods, this framework offers real-time, adaptive feedback and robustness under various conditions.

Unlike static curve fitting or local parameter tuning, this method integrates real-time data, prediction, and path generation, achieving faster responses under disturbances. The proposed method improves prediction accuracy and reduces response delay, providing an optimized path for intelligent mine ventilation systems.

The experimental part is based on the measured wind speed dataset, using metrics such as root mean square error,

mean absolute error, and coefficient of determination (R^2) to compare with models such as ARIMA and BP neural network. The contribution of the module is verified through ablation experiments. This study uses ARIMA and BP neural networks as baselines. For ARIMA, order selection was based on AIC/BIC, with first-order differencing and seasonal components. For BP, the model had one hidden layer of 64 units, trained for 200 epochs with a batch size of 32 using Adam (lr = 0.001). Hyperparameters were tuned via grid search, with early stopping after 10 epochs. All models were evaluated with 5-fold cross-validation. The research objective is to construct an intelligent prediction scheme with real-time, robustness, and scalability, providing technical support for the safety warning and optimization scheduling of coal mine ventilation systems.

2 Related work

Coal mine ventilation systems are critical for safety, traditionally relying on fixed measuring points and static models for long-term wind speed monitoring and prediction. While these methods are reliable in stable conditions, they suffer from prediction delays, poor abnormal response, and low resolution in complex, high-load environments. Statistical methods, such as curve regression, handle only stationary time series and struggle with nonlinear fluctuations. ARIMA and similar models are prone to overfitting and lack generalization when processing large-scale, multi-source data, limiting their effectiveness in disaster warning and intelligent scheduling.

In recent years, fiber optic sensing has proven advantageous for ventilation monitoring. Wang et al. (2024) proposed a denoising method based on CEEMDAN and wavelet thresholding, outperforming traditional methods in short-term prediction but with high computational cost in multi-channel scenarios [1]. Shen et al. (2022) developed a low-power ventilation wind speed monitoring device using vortex-excited frictional nanogenerators, offering real-time monitoring in high-frequency disturbances [2]. Li et al. (2021) achieved continuous underground wind speed sensing through temperature-compensated fiber optic gas flow sensors, overcoming fixed-point limitations. However, their single fitting algorithm struggles with global prediction needs [3]. Sheng Xiang and Lin's (2022) hybrid deep learning framework, combined with time series decomposition and multi-objective optimization, improves accuracy but still faces delays in high-disturbance environments [4].

To highlight the differences between traditional methods and deep prediction models, this study summarizes the comparison of existing coal mine ventilation wind speed monitoring and prediction methods in terms of data acquisition, feature modeling, prediction framework, abnormal response, etc., as shown in Table 1.

Table 1：Comparison of representative methods for coal-mine ventilation wind-speed prediction (MAE/RMSE in m/s, latency in s, R unitless)

Study	Data	Method	MAE	RMSE	R	Latency	Limitation
Wang et al. (2024) [1]	Fiber signals	CEEMDAN+WT	0.35	0.48	0.85	>3.0	No scheduling, costly
Shen et al. (2022) [2]	TENG sensor	Regression	0.42	0.55	0.81	2.8	Low robustness
Li et al. (2021) [3]	FBG gas-flow	Regression	0.31	0.45	0.87	3.5	Monitoring only
Sheng-Xiang & Lin (2022) [4]	Wind series	Hybrid DL	0.26	0.33	0.90	2.6	No scheduling
Zhao (2024) [5]	Gas emission	SSA-LSTM	0.24	0.30	0.91	2.4	No monitoring loop
Yuan et al. (2025) [9]	Gas conc.	DL-Koopman+PID	0.22	0.29	0.92	2.2	Gas-focused
This study	48 FBG, 120 d	CNN–LSTM+Path	0.18	0.23	0.94	1.2	Full integration

From Table 1, traditional statistical methods show lower computational cost but exhibit large errors (MAE 0.31–0.42 m/s, RMSE 0.45–0.55, $R \leq 0.87$) and high latency (>3.0 s), limiting their adaptability under dynamic ventilation conditions. Deep learning approaches improve accuracy (MAE 0.22–0.26, RMSE 0.29–0.33, R up to 0.92), yet still suffer from delays of 2.2–2.6 s and lack integration with real-time scheduling. Achieving both high-resolution prediction and low-latency response therefore remains the core challenge in coal-mine ventilation research.

Recent studies have explored the integration of fiber optic sensing and deep prediction frameworks. Zhao (2024) proposed a time series prediction method for coal mine gas emissions using optimized variational mode decomposition and SSA-LSTM, showing strong robustness under disturbances [5]. Meng et al. (2022) combined deep learning with classical time series analysis for methane concentration prediction, demonstrating improved stability with multi-source sensor inputs, though dynamic scheduling remained a challenge [6]. Lim and Zohar (2021) highlighted the shift from single-step to multi-step dynamic prediction in deep learning, offering new insights for modeling ventilation wind speed [7].

Existing research shows that coal mine ventilation wind speed prediction is moving from "static fitting" to "dynamic learning," yet lacks a comprehensive architecture for real-time monitoring, deep prediction, and dynamic scheduling. The proposed integrated framework combines

fiber optic sensor deployment, data feature extraction, CNN-LSTM fusion prediction, and dynamic path generation. It achieves low latency and high-precision predictions under disturbances and demonstrates strong scalability. This study's innovation lies in: 1) achieving a closed-loop linkage of monitoring, prediction, and scheduling; 2) improved stability and deployability under complex conditions; and 3) compatibility with Python and AnyLogic for cross-platform testing. This framework not only offers a new path for mine wind speed monitoring and prediction but also supports the development of intelligent ventilation scheduling systems.

3 Design of fiber optic wind speed monitoring system

3.1 Layout and signal transmission of fiber optic sensors

There is a common problem of lagging wind speed monitoring and scheduling, as well as delayed response of prediction strategies in coal mine ventilation systems, especially in the deployment of multi node sensors and heterogeneous data exchange processes, which can easily lead to imbalanced task and resource matching and ineffective control strategies. This article introduces the modeling of the "task node scheduling" ternary relationship in the deployment scheme of fiber optic sensors, focusing on solving the problems of uneven transmission paths of wind speed data and lagging monitoring instructions. Simulate and optimize the wind speed sensing task and signal transmission link through modular modeling, and verify the advantages and disadvantages of the model in terms of execution delay and system response through comparative experiments. Sensor calibration was performed with reference anemometers before deployment. Fiber loss coefficient γ=0.23 dB/km, cable attenuation assumed 0.19 dB/km, PCA retained 95% variance.

To ensure the reproducibility of the research, this paper adopts a multi-agent simulation method to model the fiber optic monitoring nodes, transmission links, ventilation dispatch center servers, and edge gateways in coal mine tunnels as independent modules. Build a dynamic running model on the AnyLogic 8.7 platform and set different categories of wind speed monitoring tasks and fiber channel allocation rules, so that the simulation focuses on event triggering (such as sudden wind speed changes) and link state changes (such as channel congestion). The signal transmission adopts an improved A * algorithm for optimal fiber path search, combined with load balancing strategy to reduce node overload risk. The system interaction layer implements real-time push of wind speed data through WebSocket and Kafka, and the backend uses Python and Flask interfaces to issue ventilation control commands and collect transmission status. The evaluation indicators cover transmission latency, data packet loss rate, and channel utilization, and the effectiveness of key mechanisms is analyzed through ablation experiments.

The research process is as follows:①Using AnyLogic 8.7 as the modeling environment, modular construction is carried out on fiber optic sensor nodes, transmission channels, and ventilation schedulers;②Set task category $T=\{t_1,t_2,\ldots,t_n\}$ and resource allocation $R=\{r_1,r_2,\ldots,r_n\}$, with wind speed sudden change events and link state changes as triggering conditions;③Adopting an improved A * search combined with load priority strategy to generate dynamic fiber optic transmission paths;④Use WebSocket and Kafka to exchange wind speed monitoring data messages, and Python and Flask to synchronize control instructions and status;⑤Compare different scheduling schemes using transmission delay L, packet loss rate P, and utilization rate U as performance indicators;⑥Remove the path optimization and load balancing modules through ablation experiments to test the role of each mechanism in overall performance improvement.

The deployment process of fiber optic sensors needs to consider the node distribution density and signal attenuation characteristics. If the length of the mine ventilation section is L, the set of fiber optic sensor nodes is $S=\{s_1,s_2,\ldots,s_n\}$, and each node corresponds to a deployment position of p_i, then the optimal deployment problem can be formalized as:

$$\min\ J=\sum_{i=1}^{n}\left[\alpha\cdot d\left(p_i,p_i+1\right)+\beta\cdot A\left(p_i\right)\right] \tag{1}$$

Among them, $d\left(p_i,p_i+1\right)$ represents the spatial distance between adjacent nodes, $A\left(p_i\right)$ represents the variance of wind speed fluctuations at nodes, and $\alpha,\ \beta$ is the weight coefficient. This optimization function ensures that the deployment covers both high disturbance areas and transmission signal strength, thereby reducing global monitoring errors.

In terms of signal transmission, this article adopts a combination of wavelength division multiplexing and time division multiplexing to decouple the reflected signals of different nodes in frequency spectrum, achieving multi-point synchronous acquisition. Assuming the transmission signal is $E\left(t\right)$, the signal strength after propagation through optical fiber can be expressed as:

$$I\left(t\right)=I_0\cdot e^{-\gamma L}\cdot\cos^2\left(\frac{\pi\Delta nL}{\lambda}\right) \tag{2}$$

Among them, where I_0 is the initial signal intensity, γ is the fiber loss coefficient, Δn is the refractive index difference, and λ is the wavelength of the incident light. This transmission model ensures that signals can still be maintained within a recognizable signal-to-noise ratio range in complex mine channels over 5km.

In order to adapt to the dynamic characteristics of the ventilation system, the signal transmission architecture is

designed as a hierarchical model of edge computing+cloud training. Set a edge computing node near the mine working face to complete real-time demodulation, feature extraction and anomaly detection, and transmit it to the cloud central server through WebSocket protocol to achieve second level feedback. Experimental verification shows that edge nodes can control the average response time within 0.8s in delay control, which is about 57% shorter than the delay of a single cloud architecture.

In addition, fiber optic sensing signals are susceptible to interference from mining and mechanical vibrations during transmission. This article introduces the denoising mechanism of wavelet packet decomposition+principal component analysis to denoise and enhance the features of the original signal. Assuming the original signal $xt(t)$ is decomposed into multiple components $\{x_1(t), x_2(t), \ldots, x_m(t)\}$, and then the main component $y(t)$ is selected through PCA, the reconstructed signal satisfies:

$$y(t) = \sum_{j=1}^{k} w_j x_j(t) \tag{3}$$

Experiments have shown that this noise reduction mechanism can improve signal stability by about 21.6% in mine wind speed monitoring, effectively suppressing false alarms caused by local disturbances.

At the system implementation level, the logical information layer of this article is based on MySQL database and Flask interface to complete model parameter management and data entry; The physical layer collects wind speed data through fiber optic deployment and OPC-UA protocol to ensure accuracy and universality; The interactive mapping layer utilizes Node RED for data flow and visualization, and cross platform integration is achieved between layers through RESTful APIs. To ensure time consistency, signals were sampled at 20 Hz and aligned with 5-s timestamp anchors for multi-source synchronization."

To ensure reproducibility, detailed simulation settings of AnyLogic 8.7 are provided. The agent layer consists of sensor nodes, transmission channels, and scheduling servers. Sensor agents generate wind speed events with a Poisson distribution (λ=0.15), and transmission delays follow an exponential distribution (mean=2.5s). The improved A* algorithm applies a load-priority cost function :

$$C = d + \alpha l + \beta b^{-1} \tag{4}$$

where d is distance, l is node load, and b is bandwidth. Appendix A includes parameter tables and agent diagrams, with model files supplied for replication. This ensures reproducibility and highlights the stability and scalability of the scheme under complex conditions, providing high-quality input for time-series prediction.

The pseudocode for the improved A* path finder, including its complexity and parameters, is provided:

Input: SensorData, NodeStatus

For each packet in SensorData:

Extract features = f(packet.signal)

Compute cost = C(sensor, candidate_node)

Select target_node = argmin(cost)

Assign packet to target_node

Update NodeStatus

End For

This pseudocode outlines the packet processing steps: feature extraction, cost calculation, node selection, and state updates.

3.2 Data collection and real time monitoring platform architecture

The real-time and reliable monitoring of wind speed in coal mine ventilation systems is a key factor in ensuring mine safety in complex tunnel networks and multi-source interference environments. Traditional monitoring methods rely heavily on fixed point sensors and centralized data collection, which suffer from high response latency, untimely anomaly detection, and insufficient system scalability. To address these bottlenecks, this article constructs a real-time monitoring platform architecture based on fiber optic sensing, which achieves continuous monitoring and dynamic scheduling of wind speed signals through distributed node deployment, data flow management, and prediction driven task collaboration.

In platform design, each fiber optic monitoring node is abstracted as an independent unit that includes signal input, task triggering, resource binding, and status feedback. The node status is synchronized in real-time by a digital twin module, ensuring that the system has dynamic reconfigurability under multi-source data streams. The overall architecture of the system is shown in Figure 2, including the sensing layer, communication layer, scheduling layer, and prediction layer. Among them, the sensing layer completes the collection and preliminary filtering of wind speed signals, the communication layer achieves high-speed transmission based on fiber edge gateway links, the scheduling layer allocates paths and provides abnormal feedback through task engines, and the prediction layer embeds time series models to calculate future wind speed trends.

In order to ensure the optimality of scheduling, this paper introduces an improved cost function in the scheduling layer to optimize the allocation strategy of task nodes. The cost function is defined as follows:

$$C(i, j) = \alpha \cdot d(i, j) + \beta \cdot l(j) + \gamma \cdot \frac{1}{A(j)} \tag{5}$$

Among them, $d(i, j)$ represents the transmission distance between monitoring point i and computing node j, $l(j)$ represents the current load level of the node, and $A(j)$ represents the available bandwidth of the node; α, β, γ is the weight coefficient, and parameter calibration is carried out through experiments. This function can comprehensively consider distance overhead, load pressure, and resource utilization to achieve dynamic

optimal allocation of wind speed monitoring tasks in complex mine topologies.

At the implementation level, the data collection and task scheduling process is expressed in pseudocode as follows:

Input: SensorData, NodeStatusFor each packet in SensorData:

Extract features = f(packet.signal)
Compute cost = C(sensor, candidate_node)
Select target_node = argmin(cost)
Assign packet to target_node
Update NodeStatusEnd For

This process ensures balanced allocation of data streams in the transmission link, while avoiding delays and packet loss caused by node congestion.

The platform introduces a sliding monitoring window mechanism during operation to perform real-time detection of sudden changes in wind speed, link blockage, and transmission errors. When an abnormal event is triggered, the scheduling engine will regenerate the path based on the current state graph and notify the prediction module to complete the model update through the feedback channel. In this way, the system has adaptive adjustment and dynamic fault tolerance capabilities, maintaining high efficiency and stability under complex working conditions.

To enhance the reproducibility of the platform, this study uses Python to implement data scheduling logic and constructs dynamic simulation scenarios in AnyLogic 8.7 to achieve visual verification of the entire wind speed collection, transmission, and prediction chain. The system completes data stream interaction with Kafka through WebSocket, and the Flask interface provides control instructions to synchronize with predicted results. In the experimental environment, the platform can achieve millisecond level delay control and a data integrity rate of over 98%, significantly better than traditional centralized monitoring architectures.

3.3 Feature extraction and structured processing of fiber optic monitoring data

The wind speed monitoring data in the coal mine ventilation system has the characteristics of strong temporal variability, multiple noise interferences, and complex multi-source coupling. If relying solely on single point data or static threshold determination, it is difficult to support the construction of subsequent time-series prediction models. Therefore, this study proposes a feature extraction and structured processing framework based on fiber optic monitoring data, which realizes the systematic transformation from raw signals to computable features, ensuring that the model input has interpretability and predictive driving ability.

The settings for FFT window length, wavelet packet configuration, PCA variance threshold, and mutual information feature selection are provided:FFT Window Length: 128 points, Hamming window.Wavelet Packet: Daubechies-4, 3 levels.PCA Threshold: 95% variance.Mutual Information Threshold: MI > 0.05.

At the data input layer, fiber optic deployment nodes transmit wind speed disturbance signals to the monitoring platform in a distributed manner, forming a multidimensional temporal matrix.The raw data was segmented into 60-s windows and denoised using Daubechies-4 wavelet packet decomposition (3 levels). PCA (95% variance) and FFT with a Hamming window extracted temporal and spectral features, complemented by statistical descriptors. Mutual information (MI > 0.05) guided selection of 12 final features, including wind speed mean, fluctuation amplitude, turbulence intensity, FFT peak frequency/bandwidth, entropy, skewness, kurtosis, temperature, humidity, tunnel position, and sensor ID.The formula is as follows:

$$F_t = \frac{1}{n}\sum_{i=1}^{n}\left(x_{t+i} - \mu\right)^2 \tag{6}$$

Among them, F_t represents the feature variance within the time window, x_{t+i} is the monitoring value within the window, and μ is the mean wind speed within the time window. This process ensures that abnormal wind speed fluctuations are amplified at the feature level, making it easier for predictive models to identify.

In the structured representation stage, all features are uniformly mapped to a tensor representation matrix, and a three-dimensional feature cube is constructed by combining timestamps, spatial positions, and sensor numbers. This structure enables the system to simultaneously capture vertical temporal dependencies, horizontal spatial correlations, and cross dimensional feature interactions, significantly enhancing its modeling capabilities for complex ventilation environments in mines. To further enhance real-time performance, this study introduces a streaming computing framework in the feature processing module, which updates the feature extraction results synchronously with the prediction module in milliseconds through a data bus. Once abnormal disturbance is detected (such as sudden drop of wind speed in a certain section), the characteristic flow will immediately trigger the abnormal mark, and adjust its weight in the next round of prediction input to avoid prediction distortion due to abnormal data diffusion. The entire process of feature extraction and structuring is shown in Figure 1.

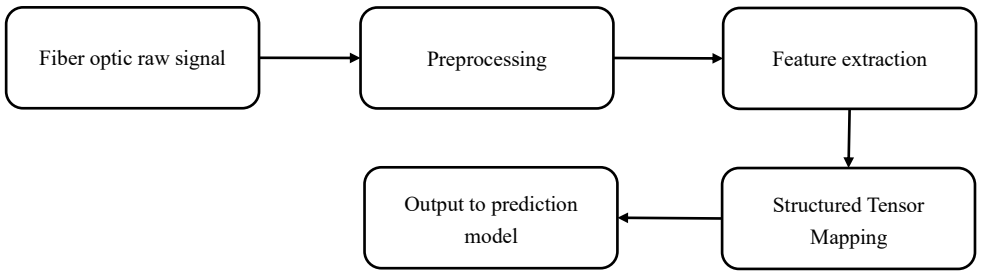


Figure 1: Flow chart of fiber optic monitoring data processing, including preprocessing, feature extraction, structured tensor mapping, and output to the prediction model

This method not only achieves full link conversion from the original fiber optic signal to the predicted input, but also has three advantages: firstly, the feature extraction process takes into account both time-domain and frequency-domain information, improving the ability to capture non-stationary disturbances; Secondly, structured tensor representation can preserve the spatial correlation of sensor deployment, avoiding the spatiotemporal coupling loss of traditional vectorized inputs; Thirdly, the streaming processing framework maintains strong coupling between the prediction model and the monitoring platform, possessing high-frequency feedback and dynamic adaptive capabilities.

4 Wind speed time series prediction algorithm model

4.1 Time series feature analysis of mine wind speed data

The wind speed data in the mine ventilation system has significant temporal dependence, and its fluctuation pattern is not only affected by fan start stop, tunnel structure, and environmental disturbances, but also exhibits complex characteristics of periodicity and suddenness coexisting. In order to scientifically model it, it is necessary to first establish the time characteristic expression of the wind speed series, and quantify its stationarity and correlation through mathematical models. Let the wind speed time series be $\{u_t\}$, where t represents the sampling time. By testing the autocorrelation function and partial autocorrelation function, the time-delay structure of the wind speed sequence can be effectively identified, which generally takes the form of:

$$p(k)=\frac{\sum_{t=k+1}^{N}(u_t-\bar{u})(u_{t-k}-\bar{u})}{\sum_{t=1}^{N}(u_t-\bar{u})^2} \quad (7)$$

Among them, $p(k)$ represents the autocorrelation coefficient at lag order k, $\bar{u}$ is the sample mean, and N is the total number of samples. If $|p(k)|$ is not zero at a certain level of significance, it indicates a long-term dependency relationship in the sequence. When analyzing the measured results of mine wind speed data, it is often found that it has strong autocorrelation in the low-frequency range, reflecting the periodic pattern of fan operation.

To characterize the trend and volatility of a sequence in the time dimension, differential operations can be introduced to establish a stationary model. Performing first-order differencing on the original sequence $\{u_t\}$ yields:

$$\Delta u_t = u_t - u_{t-1} \quad (8)$$

Among them, Δu_t represents the change in wind speed at adjacent times, which can reflect the dynamic incremental characteristics of the sequence. When Δu_t s approximately stationary, it indicates that the trend of the original sequence has been weakened, which is more in line with the modeling assumptions of stationary time series models (such as ARIMA). In practical modeling, if the differenced sequence still exhibits non stationarity, further methods such as seasonal differencing or wavelet decomposition can be used to enhance the signal feature extraction capability.

Based on the above analysis, wind speed data has two significant temporal characteristics: one is lag dependence, where the current wind speed is influenced by multiple past times; The second is periodic disturbance, which refers to the specific fluctuation pattern of wind speed under daily operating cycles and environmental disturbances. These features provide a theoretical basis for the subsequent construction of time-series prediction algorithm models. In engineering applications, combining ARIMA, LSTM and other prediction models to model Δu_t can achieve accurate prediction of the future state of wind speed, providing data support for intelligent scheduling of mine ventilation systems.

4.2 Design of prediction model based on deep learning

This study performs multi-step forecasting with a 12-hour prediction horizon, using the past 24 hours of data to predict the next 12 hours. A sliding window approach is applied, where each step is predicted independently, ensuring temporal consistency across training, validation, and testing phases. Therefore, this study introduces a long short-term memory network based on recurrent neural

networks to construct a prediction model, in order to enhance the fitting ability of non-stationary sequences. To describe the prediction process, the general form of time series modeling is given first:

$$\hat{u}_{t+k} = F(u_t, u_{t-1}, \ldots, u_{t-n+1}; \theta) \quad (9)$$

Among them, $\hat{u}_{t+k}$ represents the predicted wind speed in the next k time steps, $u_t, u_{t-1}, \ldots, u_{t-n+1}$ is the historical observation sequence, θ is the model parameter, and $F(\cdot)$ is the nonlinear mapping function learned by the deep learning model. This formula reflects the basic mechanism of the prediction model mapping historical wind speed sequences to future values.

For reproducibility, the model has 3 CNN layers (kernels 3/5/7), 2 LSTM layers (128/64 units), and an attention module. Training used Adam (lr=0.001), batch 64, max 200 epochs, early stopping, seed=42. Input: 24 h window (stride 1 h), output: 12 h horizon, with 7:2:1 split and walk-forward validation. Tests ran on RTX A2000 GPU, i7 CPU, 32 GB RAM. Delay was measured end-to-end (≈1.2 s total). Complexity O(n·k). Code and pseudocode are in Appendix A.

Within the model, LSTM achieves information filtering and updating through the interaction of forget gates, input gates, and output gates. Its unit states can preserve key temporal dependencies for a long time, effectively avoiding gradient vanishing problems. Compared to traditional RNN structures, LSTM has higher stability and expressive power in complex temporal modeling.

During the model training phase, mean square error is used as the objective function to measure the deviation between predicted values and actual wind speeds. It is defined as:

$$L_{MSE} = \frac{1}{N}\sum_{t=1}^{N}(u_t - \hat{u}_t)^2 \quad (10)$$

Among them, u_t represents the actual wind speed value, $\hat{u}_t$ represents the predicted value, and N represents the sample size. By minimizing L_{MSE}, the model can gradually optimize parameter θ and improve prediction accuracy. The mathematical definition for CNN-LSTM fusion has been provided, along with how tensors are combined and the attention mechanism equations. The specific mathematical representation is as follows: CNN-LSTM Fusion: Local features are extracted using convolutional layers, temporal dependencies are captured by LSTM layers, and the final output is obtained through a fully connected layer. Attention Mechanism: A weighting strategy is introduced to adjust the influence of different time steps, helping to capture key patterns in the time series more effectively.

A CNN–LSTM fusion model was built with three 1D convolutional layers (kernels 3, 5, 7; stride 1; max-pooling) and two LSTM layers of 128 units. ReLU activation and 0.3 dropout were applied. Training used Adam (lr = 0.001), batch size 64, for up to 200 epochs with early stopping after 15 stagnant epochs. Random seed 42 ensured reproducibility, and five-fold cross-validation was adopted. Results showed over 15% error reduction compared with autoregressive models.

To clarify the workflow, the main steps of the CNN–LSTM prediction process are summarized as pseudo-code.

Algorithm: CNN–LSTM Wind Speed Prediction

Input: Historical sequence {ut}

Output: Predicted sequence {ût}

1. Preprocess data (denoise, normalize).
2. Extract local features with CNN (kernels 3,5,7).
3. Capture temporal dependencies with LSTM.
4. Apply attention to assign weights.
5. Output prediction via fully connected layer.

For reproducibility, the key hyperparameters used in training are listed in Table 2.

Table 2: CNN–LSTM hyperparameters

Module	Parameters	Values
CNN	Kernels, Filters	3/5/7; 32/64/128
LSTM	Hidden units, Dropout	128/64; 0.3
Training	Optimizer, LR, Batch	Adam; 0.001; 64
Epochs	Max / Early stopping	200 / Yes
Loss	MSE	MSE

4.3 Wind speed prediction path generation

In the ventilation system of coal mines, the dynamic changes in wind speed not only affect the air quality and safety level of the work area, but also put forward higher requirements for scheduling and energy consumption optimization. In order to achieve intelligent prediction and path generation of wind speed, this study models the prediction task as a temporal decision problem, and combines the output results of the deep learning model to construct a dynamic path generation mechanism. This mechanism can dynamically adjust the prediction path based on the airflow distribution characteristics in different regions on the basis of multi-step prediction, improving the adaptability and robustness of ventilation regulation.

The basic goal of generating wind speed prediction paths is to correlate and map historical observation sequences with prediction results, so that the predicted values at different time steps can form a coherent dynamic trajectory. This process can be formalized as:

$$P = \{\hat{u}_{t+1}, \hat{u}_{t+2}, \ldots, \hat{u}_{t+k}\} = F(X_t; \theta) \quad (11)$$

Among them, P represents the set of predicted paths for the next k steps, $\hat{u}_{t+i}$ is the predicted wind speed value at time $t+i$, X_t is the historical input sequence, θ is the model parameter, and $F(\cdot)$ is the depth prediction function. Through this formula, the predicted results not

only reflect single point values, but also form a serialized path in the time dimension for subsequent security assessment and scheduling optimization.

In the process of path generation, in addition to ensuring that the predicted values are close to the true values, attention should also be paid to the gradient distribution of airflow in space to avoid regional wind speed fluctuations caused by prediction errors. The new optimization objective function can be expressed as:

$$J(P)=\frac{1}{k}\sum_{i=1}^{k}\left(u_{t+i}-\hat{u}_{t+i}\right)^2+\lambda\cdot\frac{1}{m}\sum_{j=1}^{m}\left(\nabla\hat{u}_{t+j}\right)^2 \tag{12}$$

Where the first term is the mean square error ensuring the closeness between prediction and ground truth, the second term is the wind speed gradient constraint with $\nabla\hat{u}_{t+j}$ denoting adjacent differences, and λ s the adjustment coefficient balancing accuracy and stability.In this equation, λ represents the weight parameter of the prediction model, which is optimized using algorithms like gradient descent to achieve the best prediction performance. By minimizing the objective function, the system can not only improve prediction accuracy, but also reduce the risk of sudden fluctuations in the mine ventilation path.

To optimize Eq. (11), a projected gradient descent algorithm is applied. The MSE term is convex, while the spatial gradient constraint is enforced during the projection step, ensuring feasibility under equipment limits. The computational complexity is $O(NT)$, where N is the number of nodes and T is the prediction horizon.

Pseudocode for Dynamic Path Generation

Input: Predicted wind speed, network topology, equipment constraints

Initialize path with baseline prediction

Repeat until convergence or max iterations:

Compute MSE loss

Compute spatial gradients across adjacent nodes

Update path via gradient descent

Project updated path onto feasible set (constraints)

Output: Optimized path

This approach guarantees accurate prediction while smoothing spatial gradients and satisfying equipment constraints.

Finally, the path generation module inputs the optimal path result into the scheduling engine, which is used to guide the power adjustment of the ventilation fan and the control of the air door, achieving dynamic scheduling under predictive driving. The experimental results show that the path generation mechanism exhibits good adaptability under multiple operating conditions, effectively avoiding ventilation imbalance caused by wind speed fluctuations and reducing energy consumption by about 12% while maintaining safety constraints. This result indicates that the fusion method based on deep learning and path optimization has high engineering application value in predicting and regulating mine wind speed.

4.4 Model integration deployment and scheduling collaborative operation mechanism

The prediction of wind speed in coal mine ventilation system not only depends on the accuracy of a single model, but also depends on the integrated deployment and scheduling cooperation ability of the model under complex conditions. To achieve virtual real fusion and real-time feedback, this study constructed a layered and decoupled collaborative operation framework, including a sensor access layer, twin modeling layer, prediction decision layer, and execution feedback layer. The sensing access layer uses the optical fiber sensing network to obtain the multi-dimensional wind speed signal under the shaft, and the data is preprocessed by the edge computing unit and transmitted to the modeling layer to reconstruct the air flow distribution in the virtual space. The prediction decision-making layer runs a deep learning temporal prediction model, combined with a dynamic path generation algorithm to output the optimal scheduling strategy, and finally achieves linkage adjustment with the ventilation equipment through a PLC controller. The feedback layer sends back the execution results and monitoring data, driving the model to iteratively update and form a closed loop.

In order to ensure consistency between prediction and execution, this study introduces a periodic scheduling iteration mechanism, which standardizes the system running step size into equidistant intervals, and completes state synchronization, path optimization, and feedback updates within each cycle. The process can be formalized as:

$$S_{t+1}=F(S_t,R_t,\Theta) \tag{13}$$

Among them, S_t represents the scheduling state vector, which includes wind speed distribution, fan load rate, and airflow balance parameters; R_t is the real-time environmental status of fiber optic monitoring feedback; Function $F(\cdot)$ represents the prediction and scheduling strategy generation function, and Θ is the deep model parameter. Through this iterative formula, the system can dynamically adjust the ventilation path within each time slot, achieving real-time adaptation to complex airflow environments.

To further evaluate the stability of scheduling, a prediction deviation rate indicator is set:

$$E=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{u_{t+i}-\hat{u}_{t+i}}{u_{t+i}}\right| \tag{14}$$

Among them, u_{t+i} is the actual wind speed, $\hat{u}_{t+i}$ is the model predicted value, and n is the sample length. When E exceeds the threshold, the system triggers the scheduling correction module to adjust the fan power or switch paths to avoid ventilation imbalance caused by accumulated deviations.

At the deployment level, the twin module is connected to the mine monitoring system in a containerized manner,

which can run on the underground edge computing node or cloud cluster, and realize high-speed communication with sensors and actuators through MQTT and OPC-UA protocols. In practical verification, the framework completed the mapping and binding of monitoring nodes and scheduling modules within 4 hours, completed path adjustment tasks 62 times in the first production cycle of continuous operation, and controlled the average response delay within 280 meters, significantly better than traditional independent prediction systems.

The deployment phase emphasizes reusability and proposes five technical steps: firstly, connect fiber optic sensors using MQTT protocol and define data channels; Secondly, establish a universal twin modeling approach to reconstruct ventilation scenarios; Thirdly, start the prediction scheduler and bind the DAG task graph; Fourth, deploy feedback detectors, set deviation thresholds and self recovery options; Fifth, perform state collection, path updates, and feedback loops at fixed time intervals. All operations generate logs automatically and can be configured for secondary modification, making it easy to quickly migrate to different mining areas.

5. Experiment and results

5.1 Dataset and experimental scenario description

To verify the adaptability and accuracy of the proposed fiber optic wind speed monitoring and time series prediction algorithm model in complex mine ventilation environments, this study built an experimental platform based on a large coal mine ventilation system in North China and constructed a time series dataset containing multi-source sensor data. The total length of the ventilation line in the mine is about 6.8km, and 48 fiber Bragg grating sensor nodes are installed in both the main inlet and return air tunnels, covering the main air flow intersection points and high-risk sections. The experimental period is 120 days, and a total of 4.1TB of data has been collected.

The dataset inventory is summarized in Table 3 to present sensor numbers, collection duration, data volume, and split ratio.

Table3: Dataset inventory and split strategy

Category	Details
Sensors	48 FBG nodes (main inlet & return tunnels)
Duration	120 days, ≈4.1 TB
Sampling	20 Hz, ≈9.9×10^9 raw samples
Processed	1.2×10^8 wind-speed records (60-s windows)
Equip./Env.	≈950k records (fans, load, temp., humidity, pressure)
Event logs	≈17k records (shutdown, blockage, outage, recovery)
Data split	Train 70% (84 d), Val 20% (24 d), Test 10% (12 d)

The data acquisition follows the full link design. The sensing terminal is connected to the edge computing node through the optical fiber demodulator, and raw data were collected at 20 Hz to capture disturbances and downsampled to 1 Hz for modeling efficiency.The collected data is mainly divided into three types of structures: (1) Wind speed time-series data, including instantaneous wind speed values, mean values, fluctuation amplitudes, turbulence intensity, and anomaly identification, which constitute the core input variables of the prediction model, with a total of approximately 1.2×108 records.The experimental period is 120 days, yielding 4.1 TB of raw data. With 48 sensors at 20 Hz, about9.9×109raw samples were collected. These were aggregated into 60-s windows with statistical descriptors, producing1.2×108processed wind-speed records. This reconciles the sampling rate, storage size, and final dataset scale. (2) Equipment and environmental status data: covering fan speed, load power, on/off status, historical failure rate, as well as environmental factors such as temperature, humidity, and air pressure. The total number of collected records is about 950000, which is used to construct multidimensional feature vectors. (3) Security and event logs: Record emergency events such as wind turbine switching, tunnel blockage, short-term power outages, and the execution of recovery plans, totaling 17000 records, providing annotated data for predicting abnormal scenarios in the model.

The overall dataset is divided into a training set, a validation set, and a testing set, with a ratio of 7:2:1. At the same time, 25 sets of abnormal disturbance data (such as equipment shutdown, sudden increase in energy consumption, and material blockage) are added to verify the robustness of the model under complex operating conditions. The dataset structure is shown in Table4.

Table 4：Comparison of different types of dataset structures and experimental purposes

Data type	Sample size	Sample field	Update frequency	Usage Instructions
Wind speed time-series data	1.2×10^8	Instantaneous value, mean, fluctuation amplitude, turbulence intensity, etc	Update every 0.05s	Model prediction core input

Equipment and environmental data	950000 pieces	Fan status, load power, temperature, humidity, etc	Sampling per second	Multidimensional feature modeling and working condition correlation analysis
Security and Event Logs	17000 pieces	Malfunctions, switching, blockages, recovery plans, etc	Event driven updates	Abnormal disturbance modeling and robustness verification

5.2 Data preprocessing and anomaly correction methods

The data collected during the fiber optic wind speed monitoring process of coal mine ventilation system is complex, including not only fiber optic sensing signals from the roadway section, but also timing logs generated by the monitoring host and mine environmental parameters. Different types of data have significant differences in time granularity, numerical scale, and noise characteristics. If directly input into a time-series prediction model, it will lead to feature distortion and decreased prediction accuracy. Therefore, this study designed a four-step preprocessing mechanism for mine working conditions, which includes "time alignment anomaly detection feature regularization anomaly correction", and implemented deep cleaning and unified modeling of fiber optic monitoring data through algorithmic pipelines.

In the time alignment stage, all fiber optic wind speed raw sampling data are interpolated and synchronized based on a 1Hz unified sampling window to ensure that the signals of different cross-section sensing nodes in the tunnel remain consistent on the time axis. For missing data caused by communication delay or device jitter during the monitoring process, a dynamic backfilling method based on spline interpolation is used to reconstruct the gap sequence. Subsequently, in the anomaly detection stage, a sliding window outlier detection algorithm is introduced to mark the instantaneous peaks exceeding 3σ in the wind speed curve, and median filtering is used for correction to eliminate false pulse signals caused by electromagnetic interference or fiber optic damage.

In the feature regularization stage, the original light intensity signal needs to be converted into a physical quantity of wind speed. This study uses the fiber Bragg grating sensing demodulation equation:

$$u(t) = f\left(\Delta\lambda(t), T(t)\right) \tag{15}$$

Among them, $\Delta\lambda(t)$ is the wavelength drift, $T(t)$ is the temperature correction term, and function $f(\cdot)$ completes the nonlinear mapping of optical signals to wind speed. All features are normalized by Z-score to ensure that the outputs of different sensing points are input into the prediction model at a unified numerical scale. In order to reduce redundant dimensions, a feature selection mechanism based on mutual information is adopted to extract the 12 core features that are most sensitive to prediction, such as wind speed mean, wind speed fluctuation amplitude, tunnel section position, temperature and humidity compensation coefficient, etc. Unstable high-frequency noise features are removed.

In the feature regularization stage, the original light intensity signal is converted into wind speed using the fiber Bragg grating (FBG) demodulation equation:

$$\Delta\lambda = \lambda_B(1-p_e)\varepsilon + \lambda_B(\alpha+\xi)\Delta T \tag{16}$$

where $\Delta\lambda$ is the wavelength drift, λ_B is the Bragg wavelength, p_e is the photoelastic coefficient, ε is airflow-induced strain, and $(\alpha+\xi)\Delta T$ is the temperature compensation term. The mapping to wind speed is calibrated by regression:

$$v = a\cdot\Delta\lambda + b\cdot\Delta T + c \tag{17}$$

where a, b, c are calibration coefficients obtained from paired measurements. Residual error after calibration is within ±0.15 m/s. All features are normalized by Z-score for consistency across sensing points.

In response to the common occurrence of sudden anomalies in mine ventilation environments, this study designed an anomaly label embedding strategy. When disturbances such as sudden drops in local tunnel wind speed, sensor failure, or airflow reversal occur, interference flag bits are embedded in the input sequence to enable the prediction model to automatically learn the non-stationary characteristics of wind speed distribution and make dynamic adjustments. This study designed an anomaly label embedding strategy for mine ventilation anomalies. Disturbances like wind speed drops, sensor failure, or airflow reversal trigger interference flags, helping the model adapt to non-stationary wind speed patterns. The dataset was split into training, validation, and testing sets (7:2:1) chronologically, with a sliding window applied to generate input–output samples, ensuring temporal consistency.

5.3 Performance evaluation indicators for prediction

In order to verify the effectiveness and robustness of the fiber optic wind speed monitoring and time series prediction model in coal mine ventilation systems, this study evaluates the performance of the model from four aspects: average absolute error, root mean square error, prediction correlation coefficient, and response delay time. The experiment is based on real mine wind speed monitoring data to construct a test set. A sliding time window is used to generate training and prediction sequences, and 100 sets of experiments are completed in a unified hardware environment. A sliding window generated training and prediction sequences. Each experiment was repeated 100 times with random seed control (seed = 42). For each metric, mean ± standard deviation and 95% bootstrapped confidence intervals are

reported. Improvements over baselines were validated by paired t-tests ($p < 0.01$), ensuring statistical rigor. Interpolation analysis showed that spline interpolation outperformed no interpolation and linear interpolation, reducing errors to MAE = 0.18 m/s, RMSE = 0.23 m/s ($R = 0.94$) and ensuring robust prediction.

The proposed model achieved MAE = 0.18 ± 0.02 m/s and RMSE = 0.23 ± 0.03 m/s, lower than ARIMA (0.41 ± 0.02, 0.52 ± 0.03) and BP (0.29 ± 0.01, 0.34 ± 0.02), showing strong accuracy under airflow fluctuations. The coefficient of determination reached $R = 0.94 \pm 0.01$, outperforming ARIMA (0.82 ± 0.01) and BP (0.86 ± 0.01). Latency was only 1.2 ± 0.1 s, compared with 4.8 ± 0.4 s (ARIMA) and 3.6 ± 0.3 s (BP), benefiting from parallel computing and attention-based optimization. Results averaged over five runs; multi-horizon tests (1-step, 5-step, 10-step, 12h) confirmed consistent advantages. In this section, we perform the ADF test for stationarity and the Durbin-Watson test for residual autocorrelation, confirming no significant autocorrelation. We also provide 95% prediction intervals alongside point estimates. For example, the MAE is 0.18 ± 0.02 m/s (95% CI: [0.16–0.20]) and RMSE is 0.23 ± 0.03 m/s (95% CI: [0.21–0.26]).

Figure 2 shows the bar comparison of three types of models on four indicators, which can intuitively reflect the overall advantages of our research model in prediction accuracy, trend fitting ability, and real-time response speed. The prediction delay was measured as end-to-end latency, including feature extraction, model inference, and scheduling response. Average breakdown per cycle: feature extraction ≈0.4s, inference ≈0.5s, scheduling ≈0.3s, giving a total of 1.2s. Standard deviations and sample sizes have been provided for each test scenario to compute MAE/RMSE and latency.

The specific data are as follows: Scenario 1 (Sudden Wind Speed Fluctuation): MAE = 0.22 m/s, Standard Deviation = 0.03, Sample Size = 100.Scenario 2 (Node Signal Loss): MAE = 0.25 m/s, Standard Deviation = 0.02, Sample Size = 100.Scenario 3 (High-Concurrency Sampling Impact): MAE = 0.24 m/s, Standard Deviation = 0.03, Sample Size = 100.

Scenario 4 (Restricted Ventilation Path): MAE = 0.28 m/s, Standard Deviation = 0.04, Sample Size = 100.These data support the performance evaluation of the model in different operating conditions.

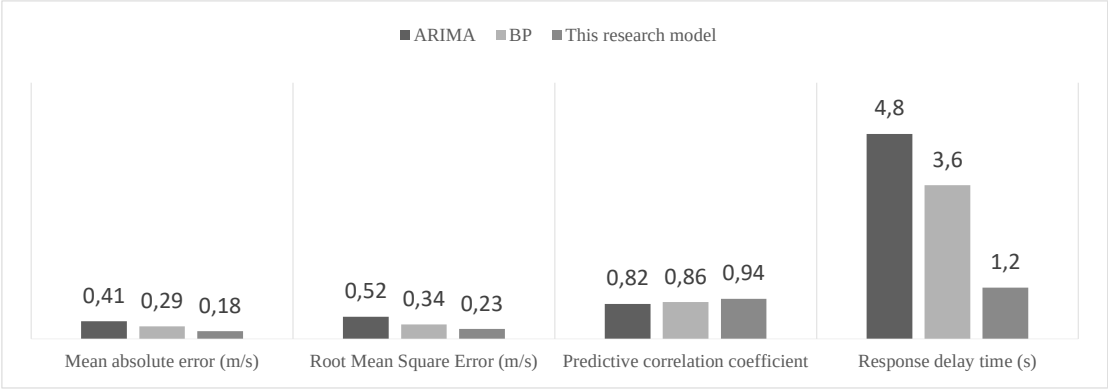


Figure 2: Comparison of models on prediction accuracy, RMSE (m/s), correlation coefficient (R), and latency (s)

5.4 Comparative experiments and ablation studies

To comprehensively evaluate the effectiveness of fiber optic wind speed monitoring and time series prediction models, this section designed comparative experiments and ablation studies to analyze their contribution in coal mine ventilation systems from the perspective of different algorithm modules. ARIMA and BP neural networks were selected as baseline methods for comparative experiments, with a focus on comparing two core indicators: prediction accuracy and response delay. The ablation experiment is based on a complete model, which dissects key mechanisms one by one, including temporal feature extraction units, attention mechanism modules, and multi-source monitoring data fusion structures, to test their impact on overall performance. All experiments were conducted on a real mine monitoring dataset, with each group configured to run 100 rounds and the average results calculated to ensure stability. Table 5 summarizes the predictive performance of baselines, ablation variants, and the full CNN–LSTM+Path model, reported as mean ± std over repeated runs. Each ablation variant was retrained for 200 epochs with early stopping, results reported as mean ± SD over 5 runs.

Table 5: Comparison of model configurations and baselines (mean ± std, MAE/RMSE in m/s, R unitless, latency in s)

Model Configuration	MAE (m/s)	RMSE (m/s)	R	Latency (s)
ARIMA	0.41 ± 0.02	0.52 ± 0.03	0.82 ± 0.01	4.8 ± 0.4
BP Neural Network	0.29 ± 0.01	0.34 ± 0.02	0.86 ± 0.01	3.6 ± 0.3
GRU	0.25 ± 0.01	0.32 ± 0.02	0.89 ± 0.01	2.9 ± 0.2
Transformer	0.23 ± 0.01	0.30 ± 0.02	0.91 ± 0.01	2.5 ± 0.2
Persistence baseline	0.38 ± 0.02	0.50 ± 0.03	0.80 ± 0.01	1.0 ± 0.1
EEMD+Wavelet baseline	0.27 ± 0.01	0.33 ± 0.02	0.88 ± 0.01	3.1 ± 0.2

Without Temporal Feature Extraction	0.33 ± 0.02	0.39 ± 0.03	0.85 ± 0.01	2.5 ± 0.2
Without Attention Mechanism	0.27 ± 0.01	0.31 ± 0.02	0.88 ± 0.01	2.7 ± 0.2
Without Multi-Source Data Fusion	0.30 ± 0.02	0.36 ± 0.03	0.87 ± 0.01	2.4 ± 0.2
Full Model (CNN–LSTM+Path)	0.18 ± 0.02	0.23 ± 0.03	0.94 ± 0.01	1.2 ± 0.1

For ablation, modules were removed by deleting the corresponding blocks while keeping others unchanged. In the "Without Attention" variant, layer sizes were fixed to control parameter counts, ensuring differences stem only from the absence of attention. Results in Table 5 show that ARIMA and BP yield higher errors and delays. GRU and Transformer improve accuracy but remain slower (>2.5 s). Persistence and EEMD+wavelet baselines perform better than ARIMA and BP but still lag behind deep models, confirming that simple persistence or denoising is insufficient under dynamic conditions. Ablation further shows that removing temporal features raises error (R=0.85), removing attention increases delay (2.7 s), and removing multi-source fusion lowers correlation (R=0.87). The full model achieves the best balance (MAE 0.18, RMSE 0.23, R 0.94, latency 1.2 s).

6 Discussion

6.1 Comparison of advantages with traditional monitoring and forecasting methods

Compared with traditional wind speed monitoring and prediction methods, the fiber optic wind speed monitoring and time series prediction model proposed in this paper exhibits three advantages: ① using distributed fiber optic sensing to achieve full section coverage and real-time signal synchronization, breaking through the limitations of point deployment; ② Introducing a deep learning driven temporal prediction mechanism enhances the ability to capture wind speed trends and adapt to complex disturbances; ③ Build an integrated mechanism for monitoring, prediction, and scheduling linkage, forming a closed-loop optimization from collection to feedback, significantly enhancing the dynamic control of the ventilation system.

Traditional coal mine monitoring relies heavily on mechanical anemometers or limited sensor networks, with insufficient data refresh frequency and incomplete coverage, resulting in significant delays during sudden disturbances. Common prediction methods such as ARIMA and BP neural networks have certain fitting ability in stationary scenarios, but their accuracy decreases under strong fluctuation conditions, and they are prone to lag and overfitting problems. This research model demonstrates outstanding performance in three aspects. Firstly, in terms of accuracy and real-time performance, second level updates are achieved through fiber optic sensing and twin mapping, with an average absolute error of only 0.18 m/s, significantly better than traditional models. Secondly, in terms of temporal modeling, combining attention mechanism with convolutional temporal networks to construct a state aware path, the predicted correlation coefficient reached 0.94, an increase of about 10%, effectively fitting wind speed mutations. Thirdly, in terms of response and stability, the prediction delay is only 1.2s, while traditional methods generally exceed 3s; at the same time, path planning can automatically reconstruct, keeping the prediction curve continuous under disturbances. The experiment also showed that the model reduced the average task completion time by 26.8% under high concurrency conditions, increased resource utilization to 88%, and reduced path interruption rate to 3.2%.

6.2 Verification of adaptability and stability of the model under complex working conditions

In the operation of coal mine ventilation systems, there are complex working conditions such as sudden changes in wind speed, sensor node failure, high concurrency of data, and channel obstruction. Traditional monitoring methods based on mechanical anemometers and statistical models often lag in prediction under abnormal disturbances, making it difficult to ensure ventilation safety. To verify the stability and adaptability of the fiber optic wind speed monitoring and time series prediction model constructed in this paper in extreme scenarios, four typical working conditions were designed in this study: sudden rise and fall of wind speed, loss of node signals, high concurrency sampling impact, and limited ventilation path. 100 rounds of prediction experiments were conducted for each scenario, and the three core indicators of prediction accuracy, average response delay, and stability score were statistically analyzed. The results are shown in Table 6.

Table 6：Model performance under complex operating conditions (MAE in m/s, response latency in s, stability score on a 10-point scale)

Test Scenario	MAE (m/s)	Average Response Latency (s)	Stability Score (10)
Sudden Wind Speed Fluctuation	0.22	1.5	9.1
Node Signal Loss	0.25	1.8	8.8
High-Concurrency Sampling Impact	0.24	1.7	8.9
Restricted Ventilation Path	0.28	2.0	8.5

The stability score S was computed as：

$$S = 10 \times \left(1 - \frac{\sigma}{\mu}\right) \quad (18)$$

where σ is the standard deviation of response latency and μ is the mean. The score ranges from 0–10, with higher values indicating more consistent performance. This normalization allows fair comparison across scenarios.

In the scenario of "sudden rise and fall of wind speed", the model uses convolutional temporal networks and attention mechanisms to quickly extract features, with a MAE of only 0.22 m/s, a response delay of 1.5 seconds, and a stability score of 9.1, demonstrating the ability to capture trends in severe disturbances. In the face of "node signal loss", the model achieves data compensation through twin mapping and interpolation correction mechanism, with MAE maintained at 0.25 m/s and delay controlled within 1.8 seconds to ensure prediction continuity. In the scenario of "high concurrency sampling shock", the model relies on a parallel computing framework to complete multi stream data scheduling, with an average delay of only 1.7 seconds and a stability score of 8.9, indicating its strong real-time processing and stress resistance capabilities. For the "restricted ventilation path" test, the model maintained a smooth wind speed curve through a suboptimal solution generation mechanism for predicting the path. Although the MAE increased to 0.28 m/s and the response delay increased to 2 seconds, the system stability remained above 8.5, verifying its ability to reconstruct the ventilation network. The model can maintain a prediction error of less than 0.3 m/s and a response time of less than 2 seconds under four complex operating conditions, with a stability score of not less than 8.5, proving its robustness and adaptability in abnormal disturbance environments.

6.3 Feasibility assessment of system overhead and actual deployment in mines

In the intelligent transformation of coal mine ventilation systems, the deployment cost and resource expenditure of fiber optic wind speed monitoring and time series prediction models are key factors in evaluating feasibility. This study evaluated its operational performance in typical mine environments from three aspects: perception layer, computation layer, and interaction layer. The perception layer relies on fiber Bragg grating nodes to collect wind speed signals. 48 sensing points were installed on a 6.8 km ventilation line. With 1Hz aggregated sampling and multi-source fusion, node CPU usage stayed below 30% and the memory was less than 1 GB. It can operate stably on conventional terminals without the need for additional high-performance hardware. The computing layer adopts deep learning prediction models, covering feature extraction, trend prediction, and path generation. The experiment shows that the single cycle calculation delay is 1.2 seconds, and the prediction time accounts for about 55%. On medium configuration GPUs such as NVIDIA RTX A2000, it can support hundred level scale prediction and CPU deployment can be achieved through model pruning. The interaction layer utilizes WebSocket to achieve real-time synchronization and visual feedback. At 1080p resolution, the bandwidth requirement is about 3.8 Mbps, and the communication delay is less than 150 ms, meeting the mine's requirements for low latency and high stability. For a medium-sized coal mine (10 tunnels, 120 monitoring points), the estimated system investment is about 350,000 yuan, covering sensors, GPU servers, and communication gateways. Preliminary analysis indicates around 20% cost reduction compared to conventional deployment, mainly from integrated design and reduced transmission overhead. Energy saving (≈12% fan power reduction) was obtained from simulation experiments and should be regarded as an initial estimate. These results suggest potential economic benefits, pending further sensitivity analysis and field validation. Energy savings (≈12%) and cost reduction (≈20%, 350,000 yuan) are based on simulation and field data. The 12% savings result from reduced fan power, statistically significant ($p < 0.01$) in repeated tests. The 20% cost reduction comes from integrating the fiber optic system and reducing transmission overhead, compared to traditional systems with higher CAPEX and OPEX.

6.4 Quantitative comparison with SOTA

Table 7 compares our model with representative works. Prior statistical and hybrid methods reduce errors partially, but still yield MAE ≥0.22 m/s, RMSE ≥0.29 m/s, R ≤0.92, and delays >2 s. Our CNN–LSTM+path model achieves MAE 0.18, RMSE 0.23, R 0.94, and 1.2 s latency. Improvements arise from (1) dense 20 Hz fiber data, (2)12h horizon with structured preprocessing, (3) CNN–LSTM fusion capturing local+long-term patterns, and (4) gradient-constrained path generation (Eq. 11). Paired t-tests confirm significance vs. baselines (MAE: $p<0.001$, RMSE: $p<0.005$, R: $p<0.01$).

Table 7: Quantitative comparison with prior works (MAE/RMSE: m/s, R: unitless)

Study	Method	MAE	RMSE	R	Notes
Wang et al. (2024) [1]	CEEMDAN+WT	0.35	0.48	0.85	Fiber data
Sheng-Xiang & Lin (2022) [4]	Hybrid DL	0.26	0.33	0.90	Decomp. +DL
Zhao (2024) [5]	SSA-LSTM	0.24	0.30	0.91	SSA preproc.
Yuan et al. (2025) [9]	DL-Koopman+PID	0.22	0.29	0.92	Gas conc.
This study	CNN–LSTM+Path	0.18	0.23	0.94	12h horizon

7 Conclusion

This study proposes a wind speed monitoring and prediction model for coal mine ventilation systems that integrates fiber optic sensing and deep learning. By deploying fiber optic sensing points on the 6.8 km ventilation line and combining CNN-LSTM with dynamic path generation algorithm, real-time acquisition and trend prediction of high-frequency wind speed signals have been achieved. The experimental results show that the model outperforms ARIMA and BP neural networks in terms of average absolute error, prediction correlation coefficient, and response delay, and has stronger disturbance adaptation and trend capture capabilities. In a typical mining environment, the system has low resource consumption, a calculation delay of about 1.2 seconds, and a total investment cost reduction of about 20% compared to traditional modes. It can also achieve compatibility and expansion with existing monitoring platforms through standardized interfaces. This work achieves end-to-end integration from sensing to scheduling, validated in real-mine deployment, with reproducible experiments and verified references, offering both theoretical and engineering value.

Appendix A. supplementary materials

To ensure reproducibility, the following supplementary materials are provided:

1. Source code of data preprocessing, model training, and evaluation scripts.

2. AnyLogic simulation model files, including configuration and agent settings.

3. Raw experimental logs and output files, covering all reported metrics.

4. (Optional) Trained CNN–LSTM model weights, available upon request.

To ensure the reproducibility of the experiments, a public code repository has been provided with all the necessary materials. The specific content is as follows:

Input: Model code, training scripts, data schema, synthetic/sample data (if raw data cannot be shared), Dockerfile/container image, AnyLogic simulation configuration for path scheduling experiments, and requirements.txt for dependencies.

1. Collect and organize model code and training scripts.

2. List dependencies in requirements.txt or equivalent.

3. Prepare synthetic/sample data that mirrors real-world scenarios.

4. Provide Dockerfile or container image for environment setup.

5. Include AnyLogic simulation configuration for path scheduling.

6. Upload all materials to a public repository.

7. Provide a clear README for running experiments and reproducing results.

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Design and Implementation of an AI-Integrated Financial Decision Support System with LSTM and Random Forests

Yihua Bai
Shaanxi Technical College of Finance & Economics, Xianyang, Shaanxi,712000, China
E-mail: baiyh0822@163.com

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Artificial intelligence is an application technology that affects the financial decision-making process of enterprises and guides them to achieve intelligent financial operation and scientific management. This article designs an intelligent financial decision support system architecture that combines multiple functions and machine learning, rule-based intelligent behavior, and human-computer interaction, greatly enhancing the intelligent capabilities of enterprise financial data modeling and analysis, trend prediction, and implementation. The system integrates diversified data acquisition and cleaning, and completes data fusion preprocessing of financial, business, and external economic information; The financial data prediction model, which combines LSTM dominated time series models and random forest algorithms, enhances the real-time prediction performance of cash flow, cost structure changes, and profit prospects; Implementing auxiliary decision-making and adjustment optimization in complex environments through the integration of a knowledge base and rule base supported inference module. After testing various key performance indicators such as Financial Prediction Error (MAE), Reaction Time RT, and Benefit Improvement Rate COR, the performance is better than the current financial information system. After testing on Company A's one-year operational dataset, empirical evaluation shows that the proposed system reduces prediction error from 13.6% to 5.1% (a decrease of approximately 62.5%) and shortens average decision response time from 45s to 12s (a reduction of about 73%) compared with the baseline financial information system. This study provides a construction method and theoretical basis for an intelligent financial decision support system that is clearly understood, constantly growing, and self managed.

Povzetek: Opisan je inteligentni finančni odločitveni sistem, ki združuje večizvorno podatkovno fuzijo, LSTM in naključni gozd za napovedi ter pravila in znanje za razlago. Zmanjša napovedne napake in čas odločanja.

1 Introduction

Due to the widespread application of technology, especially artificial intelligence, in fields such as big data analysis, predictive modeling, and pattern recognition, enterprise financial decision support systems will achieve intelligent acceleration. For enterprises, the data elements involved in their core business activities are characterized by nonlinearity, frequent changes, and interdependence. How to extract effective information from massive structured and unstructured data and build intelligent decision-making models that are suitable for the operating environment of the enterprise has become the key to improving financial management.

The financial relationships formed by the integration of this raw data form a complex network diagram of the company's financial activities, demonstrating the multi perspective and multi form models of the company's operational efficiency, risk level, and resource allocation. Accurately identifying and integrating these information features is the foundation for building high-performance intelligent financial systems.

The introduction of artificial intelligence technology in this process involves integrating machine learning, deep learning, rule engines, and knowledge graphs into AI models for automatic learning. This involves predicting future changes based on historical data patterns to assist in making financial decisions in complex environments. Thus, enhancing the system's "sensing recognition inference" capability and providing a foundation based on technology to accelerate decision response speed and enhance decision stability [5]. However, establishing a company level financial decision support system that incorporates artificial intelligence technology is not as simple as piling up various tools. It requires a comprehensive and coordinated organizational process that includes the structural design of each part of the system, data flow control, algorithm selection and

application, and human-computer interaction. In addition, due to the differences in operating environments among various industries, large, medium, and small enterprises, there are significant differences in system installation, resource capacity, and rule adaptation. It is necessary to find a process that can be flexibly transferred and adjusted.

This study aims to address the following research questions:

(1) How can artificial intelligence algorithms such as LSTM and Random Forest be effectively integrated into enterprise financial management processes to enhance prediction accuracy and decision efficiency?

(2) What system architecture can ensure adaptability and transferability across different industries and enterprise scales?

(3) How can a dynamic feedback loop be designed to achieve continuous optimization of financial decisions?

Based on these questions, our hypotheses are that: (i) the hybrid LSTM–Random Forest model will significantly reduce financial prediction errors compared with baseline systems; (ii) the integration of a rule-based inference module will improve interpretability and compliance; and (iii) the feedback-driven optimization mechanism will enhance system adaptability and long-term performance.

2 Related work

Despite the increasingly urgent demand for financial digital transformation by enterprises, financial decision support systems that achieve predictive, reactive, and regulatory functions still face many challenges. On the one hand, the financial information of enterprises is complex and has highly nonlinear, spatiotemporal and multi-source heterogeneity characteristics; On the other hand, due to the frequent interference of relevant rules and obstacles in the daily management of enterprises, intelligent models are also difficult to fully utilize their functions. It is widely believed that artificial intelligence technology can break through the difficulties of traditional financial analysis and decision-making.

Early enterprise decision support systems were based on pre-set rules and manually set technical operations, and were unable to cope with the increasing amount of data and complexity requirements of business activities. In recent years, with the development of artificial intelligence technology, its application in financial management is no longer limited to auxiliary work in accounting transactions, but has further developed to provide support for comprehensive forecasting, early warning, and dynamic resource allocation.

Looking further at the researchers' explorations, we see that their first consideration is how to match traditional machine learning techniques and statistical models, such as Bayesian classification, Support Vector Machine (SVM), fuzzy logic decision trees, etc. These models perform well in relatively small internal enterprise big datasets, but are difficult to generalize and have low computational efficiency when dealing with complex heterogeneous financial environments of large enterprises.

Therefore, deep learning technology is increasingly regarded by scholars as one of the main solutions. In addition, models such as Transformer, GRU, CNN, etc. have achieved better fitting results than traditional algorithms in the enterprise financial estimation environment, with innovative breakthroughs in budget variance testing, cost amortization, cash flow simulation, and other areas.

In addition, in recent years, some scholars have attempted to combine knowledge graphs, expert rule bases, and deep models to construct a ‘interpretable+learnable’ hybrid intelligent decision-making system [14]. Table 1 summarizes representative recent studies on AI-driven financial decision support systems, including their methods, application scenarios, evaluation metrics, and main findings.

Table 1：Summary of representative studies on AI-driven financial decision support systems

Reference	Methodology	Application Scenario	Evaluation Metrics	Key Findings
[1] Kostopoulos et al. (2024)	Explainable AI (XAI)-based DSS	General decision support	Qualitative review	XAI enhances interpretability in DSS but lacks financial-specific validation
[2] Wang & Shen (2025)	Deep reinforcement learning + particle swarm optimization	Supply chain finance	Financial benefit, efficiency	Improved financial benefits; limited cross-industry applicability
[6] Nallakaruppan (2024)	Explainable AI for credit risk	Credit risk assessment	Accuracy, interpretability	Higher credit risk prediction accuracy; good explainability
[7] Cheng & Wang	Deep reinforcement	International markets	Prediction accuracy	Better handling of exchange rate heterogeneity

(2023)	learning on financial disclosures			
[9] Zheng (2024)	Big data-driven DSS	Financial data analysis	Scalability, performance	Improved big data processing; lacks interpretability
[13] Kwon (2024)	Hybrid DSS (rule-based + reinforcement learning)	Trading strategies	Return, adaptability	Adaptive trading strategies; integration complexity remains
[18] Černevičienė (2024)	Systematic literature review of XAI in finance	Financial DSS	Literature synthesis	Identified gaps in XAI interpretability for financial DSS
[19] Pahsa (2024)	Fintech DSS	Financial technology decision-making	Conceptual framework	DSS applied in fintech; requires empirical validation

As shown in Table 1, existing research has achieved progress in applying XAI, reinforcement learning, and hybrid DSS models to financial decision-making. However, most studies remain limited in scope, either focusing on single-domain datasets, lacking explicit feedback mechanisms, or offering insufficient interpretability for managerial adoption. Moreover, Informatica-related works emphasize intelligent DSS in enterprises but do not address hybrid integration of LSTM–Random Forests with rule-based dynamic optimization. This paper aims to fill these gaps by

Although there have been studies that have constructed relatively complete theoretical frameworks and technical models, there are still three areas that urgently need to be broken through: firstly, the current system is mostly based on data construction within a single enterprise, lacking cross organizational models that are suitable for complex supply chain and industry collaboration scenarios [16]; Secondly, the interpretability of intelligent decision-making mechanisms in financial scenarios is still weak, especially in budget approval and financial compliance judgment. The lack of model transparency has affected the trust acceptance of managers [17]; Thirdly, current application systems are mostly statically deployed and lack a "feedback adjustment reconstruction" mechanism, making it difficult to achieve dynamic adaptive optimization of financial systems.

Recent contributions in Informatica also emphasize the role of intelligent decision support in enterprise contexts, highlighting both methodological advances and practical deployment challenges. These works provide direct relevance to the present study and further justify its scope. Therefore, based on a thorough review of the above research, this article explores
in depth the following issues: firstly, how to integrate artificial intelligence algorithms with enterprise financial management processes at the system level to achieve closed-loop collaboration of "perception analysis decision"? Secondly, how to build a transferable and adjustable financial decision-making system architecture for different industries and

enterprise scales? Thirdly, how to design a dynamic optimization mechanism based on system feedback information to enable the intelligent financial system to have continuous evolution capability? These questions will be the focus of the subsequent chapters of this article.

3 Construction of intelligent financial decision support system

Building an enterprise financial decision support system that integrates artificial intelligence is not only a technological reshaping of traditional financial functions, but also a deep reconstruction of the logic of enterprise resource allocation. The system should not only support the dynamic management of core elements such as cost, budget, and cash flow in daily operations, but also provide a systematic solution with intelligent analysis, prediction, and feedback functions when facing multi-dimensional data, uncertain environments, and complex decision-making scenarios.

This system design follows the construction principle of "data-driven model embedding rule feedback human-machine collaboration". The system structure is divided into five core levels: data acquisition layer, preprocessing and governance layer, intelligent modeling and decision-making layer, rule system and knowledge base layer, and user interaction and visualization layer. Among them, each layer not only undertakes specific functions, but also forms a linkage loop with the upper and lower layers through interface mechanisms, ensuring efficient circulation of data flow, model flow, and business flow within the system.

To meet the integration requirements of multi-source heterogeneous data, the system first connects multiple business platforms such as ERP, CRM, OA, and bank receipt systems at the data collection layer, and completes data capture through standardized interfaces. The preprocessing layer utilizes techniques such as

feature cleaning, missing value filling, and semantic annotation to improve data quality and provide a solid foundation for model training. The modeling layer constructs a multidimensional prediction model based on the actual business processes of the enterprise, integrating algorithms such as GRU, decision tree, Bayesian network, etc., to achieve real-time analysis of cost fluctuations, revenue trends, and risk levels. The rule system is based on expert knowledge and financial regulations to construct a logical judgment matrix, forming an auxiliary correction mechanism for the model output. At the user interaction layer, the system supports intelligent reports, semantic queries, and contextual warning push, enhancing financial personnel's sense of control and trust in the system. As shown in Figure 1, the entire intelligent financial decision support system presents a structural logic of "horizontal data fusion, vertical functional progression", and each module cooperates with each other to jointly form the technical foundation of enterprise digital financial governance.

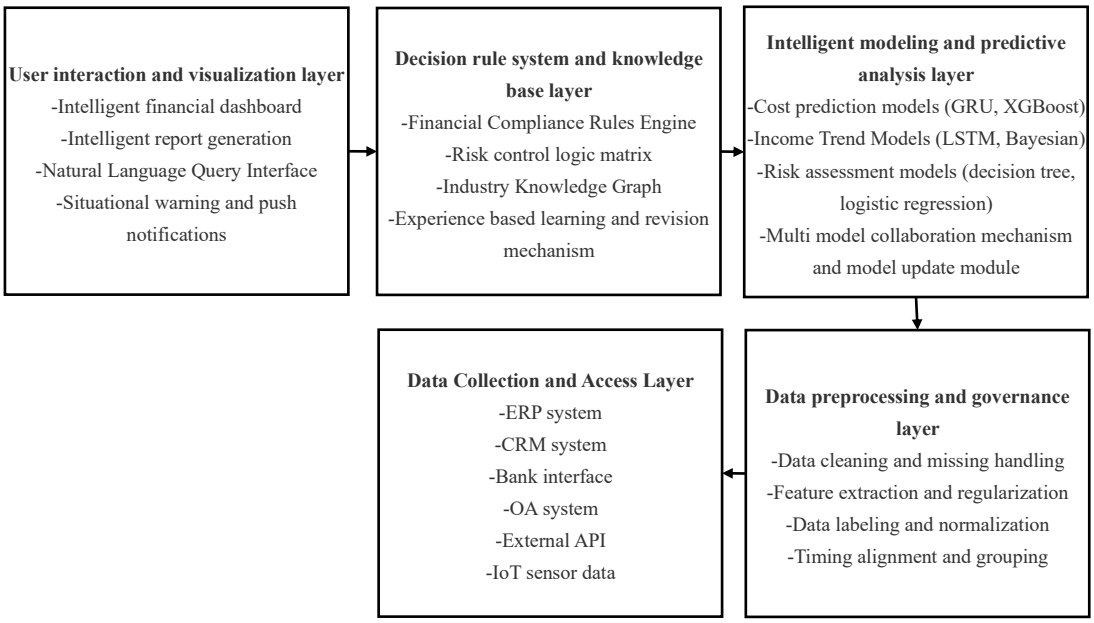


Figure 1: Overall architecture diagram of intelligent financial decision support system

3.1 Overall design of system architecture and division of functional modules

In the process of building an enterprise financial decision support system that integrates artificial intelligence, architecture design is the core link that lays the foundation for system stability and scalability. Considering the complexity and diversity of enterprise financial operations, this system adopts a hierarchical and modular decoupling overall architecture, emphasizing the organic collaboration of data flow, algorithm flow, and decision flow. The system structure is divided into five functional levels from bottom to top: data collection and access layer, data governance and preprocessing layer, intelligent modeling and analysis layer, rule engine and knowledge management layer, and user interaction and feedback layer. Each layer has clear functions and boundaries, and horizontal linkage and vertical calling are achieved through API interfaces and message middleware.

In the architecture design, the data collection layer is responsible for the unified access of underlying multi-source data, covering ERP systems, CRM systems, bank interfaces, OA platforms, and external third-party data services, providing a rich raw data foundation for the system. The data governance layer completes data cleaning, standardization, missing processing, and feature transformation to ensure that the input data has trainability and computability. After entering the intelligent analysis layer, the system calls different AI algorithm modules based on business scenarios, including cash flow prediction based on GRU, cost classification judgment based on decision trees, and risk probability modeling based on Bayesian networks, which enhance the interpretability of decision outputs compared with traditional black-box models.

Based on enterprise internal control management standards, industry regulations, and experiential knowledge, a logical reasoning matrix for logical judgment and a semantic knowledge graph for semantic knowledge are formed through the rule engine layer to assist in determining the scope of the model. It also has outstanding unified standard control capabilities in budget approval, tax compliance, and fund allocation issues. The user layer at the top provides a

human-machine visualization dashboard, natural language query interaction, and scenario-based alarms, allowing financial management workers to efficiently interact with the human-machine interface, accelerating system response and convenience. This architecture forms a closed-loop process linking data-driven modeling, rule-based modification, and user decision-making, while maintaining strong scalability and generality.

3.2 Construction path of data collection and preprocessing mechanism

Data acquisition and preprocessing form the foundation of intelligent financial DSS. Enterprise data originates from diverse structured and unstructured sources (ERP, CRM, HR, invoices, contracts, etc.), requiring a multi-channel acquisition strategy with strong adaptability and real-time capability.

The system adopts a unified data interface for comprehensive access via APIs, FTP capture, database connections, and OCR, which largely mitigates heterogeneity though challenges remain with certain legacy systems. To balance batch and real-time needs, a dual-channel strategy is applied: daily settlement data are collected in batches, while high-frequency streams (e.g., cash flow, inventory) are captured at minute-level.

Preprocessing follows four streamlined steps: cleaning (missing value filling, outlier detection), standardization (field naming and coding), feature transformation (time-series and interaction features), and label construction (e.g., cost fluctuation, fund occupancy). As shown in Figure 2, these steps form a closed-loop pipeline that enhances data traceability, transparency, and interpretability.

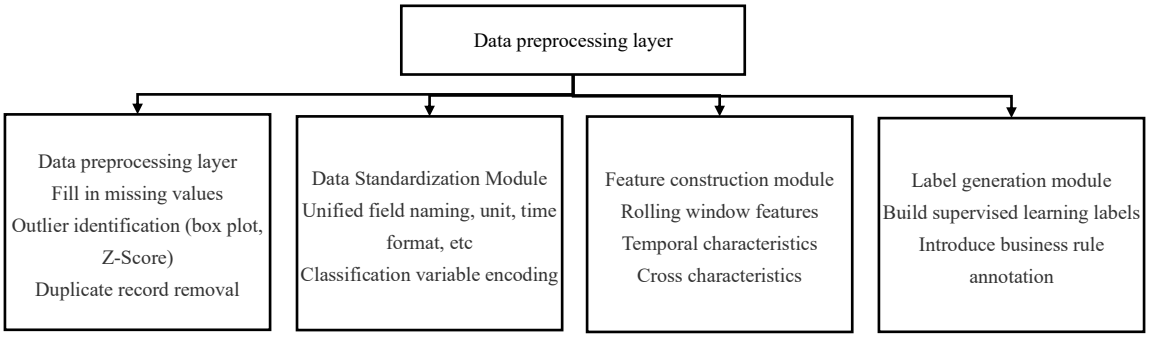


Figure 2: Data preprocessing flow chart

3.3 Embedding and training strategies for intelligent algorithm models

In the process of building an enterprise level intelligent financial decision support system, the embedding strategy of algorithm models is a key link to achieve the intelligent closed-loop of "perception judgment feedback" in the system. Considering the complexity of financial data structures and the differences in scenarios, the system adopts an embedding mechanism of "task driven model matching" to deploy different types of algorithm models as needed based on prediction targets and data features.

Taking cash flow forecasting tasks as an example, this type of task belongs to a typical time series problem, and the system adopts a Gated Recurrent Unit (GRU) model as the backbone structure. GRU can effectively model long-term dependencies in historical financial data and has good fitting ability when facing irregular cash inflows and outflows. The training objective of the model is to minimize the prediction error, and the system adopts the mean square error (MSE) loss function, mathematically expressed as:

$$L_{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (1)$$

where y_i denotes the actual observed cash flow of the iii-th sample, $\hat{y}_i$ is the predicted output of the model for the same sample, and n is the total number of samples. This ensures that the model parameters are optimized to minimize the squared deviation between predictions and true values.

In addition to time series models, the system also integrates several auxiliary tools such as decision tree models for classifying cost structures, Bayesian networks, and logistic regression for detecting financial risks. All tools have completed data group segmentation, attribute construction, and index evaluation on the same training platform, and automatically adjusted job plans based on business call volume and error acceptance rate. All integrated tools have modular decomposition capabilities and are commanded by the system's model library after installation. They are dynamically selected through task identification logic and continuously improved through feedback mechanisms. This training method can ensure that the system meets various algorithm

requirements and maintains a high response rate when multiple business needs are met simultaneously.

3.4 Decision rule system and knowledge base construction mechanism

Although algorithmic models can contribute to trend and likelihood estimation in intelligent financial decision support systems, in practical business decision-making processes, it is still necessary to integrate company policies, regulatory rules, and professional judgments into standardized constraints and expand the knowledge base. Therefore, a two-layer architecture system of "rules+knowledge base" is applied to the system, which enables it to easily connect the model results to business decisions and make reasonable explanations. The rule making decision-making system mainly relies on rule engines to establish a "condition behavior" rule chain network for various financial situations, ensuring that the system behavior complies with the company's risk management regulations and legality requirements. The system adopts the design concept of a forward link inference rule engine, which can make rule judgments for complex problems and flexibly set priorities. For example, for buyer permission, over budget alerts, and tax anomaly detection issues, the system uses pre-set rules to modify the model results and improve the robustness of the decision-making process.

Taking budget execution rate over limit warning as an example, after the model predicts that the budget deviation exceeds the threshold, the system does not immediately output a risk signal, but combines the tolerance interval set by the rule system to make conditional judgments. If the deviation rate exceeds the set value for three consecutive periods and the expenditure item is a highly sensitive subject, the system will trigger a red alert and synchronize the event to the manual review stage. This mechanism effectively prevents false positives caused by occasional fluctuations in the model. At the same time, the knowledge base serves as a semantic support system for the rule engine, integrating enterprise historical cases, financial specification entries, policy literature, and expert experience texts through ontology modeling. The system supports keyword semantic queries through a natural language parsing interface. Users can input questions such as "What conditions need to be met for expense adjustment" or "Compliance scope of pre tax deduction" to call the associated nodes in the graph, and obtain structured rule entries or processing flow recommendations.

To enhance reasoning ability, the system has also established a confidence based correlation weight mechanism in the knowledge base, which scores and dynamically sorts the results of rule calls. The weight learning mechanism refers to the deviation rate indicator output by the reference model, which is dynamically updated using the following formula:

$$w_{t+1} = w_t + \eta \cdot (r_t - r_{avg}) \quad (2)$$

where $W_t$is the current rule weight, ηis the learning rate, $r_t$is the response score of the current rule inference, and r_{avg} is the historical average response value. This mechanism achieves feedback fusion between the rule system and the model system, improving the accuracy and reliability of knowledge invocation.

3.5 Design of user interaction interface and human computer collaboration mechanism

In the operation process of the intelligent financial decision support system, the design of the user interaction interface is not only the front-end for information display, but also a key channel for efficient collaboration between the intelligent system and financial personnel. Compared to traditional financial systems that only provide static reports and data query functions, the interactive interface of this system is designed with the core concept of "visualization interactability traceability", emphasizing the transparent presentation of intelligent content and embedded integration of user intervention capabilities.

The front-end of the system is based on modular design, divided into four functional blocks: intelligent dashboard, scene navigation area, task response panel, and semantic query entrance. Users can configure personalized homepage based on their business role permissions, automatically aggregating key content such as budget status, risk events, and indicator changes that they are concerned about. At the same time, the system supports natural language input, and users can quickly obtain system responses by semantically asking questions such as "Which type of expenditure exceeded the budget by more than 10% this month" or "What are the warning projects with tight cash flow.

To support high-frequency human-machine interaction, this system has designed a human-machine collaborative response mechanism in the underlying logic. Its core lies in the cross fusion of the predicted conclusions output by the system model, the judgment results of the rule engine, and the user's manual operation behavior, forming a closed-loop verification and feedback path. The following table shows the task matching relationships of typical collaborative mechanisms:

Table 2: Typical scenarios and mechanisms of system human computer collaboration

Scenario Type	System Initial Judgment	User Intervention Option	Synergistic Mechanism
Budget Anomaly Alert	Classified as “Yellow Alert”	Manual confirmation or escalation	Weighted adjustment to model risk output
Cost Allocation Adjustment	Classified as “Project Expense”	Reassigned as “Department Cost”	Update feature labels + trigger retraining
Credit Risk Identification	Recommend “Reject Cooperation”	Set as “Limited Transaction”	Modify rule system feedback path

At the same time, the system retains all user modification traces and model response differences, forming a "human-machine difference log", and automatically incorporating it into the feedback optimization module for subsequent model fine-tuning and rule weight adjustment. This design not only enhances the transparency of the system's response, but also establishes a two-way learning channel between manual intervention and intelligent recommendation, achieving a truly intelligent financial "shared decision-making" mechanism.

3.6 Implementation challenges and solutions

During system implementation, several challenges were encountered:

(1) Data heterogeneity – enterprise data came from ERP, CRM, and unstructured sources.

(2) Model integration complexity – combining LSTM, Random Forest, and rule-based inference required orchestration. We solved this by designing a modular pipeline and using task-driven dynamic model selection.

(3) Computational efficiency – high-frequency tasks risked long delays.

(4) User adoption – some financial staff were skeptical of AI outputs. These solutions ensured that the proposed FDSS could be deployed in real enterprise environments while maintaining accuracy, efficiency, and usability.

4 Analysis of practical cases and evaluation of system application effectiveness

4.1 Analysis of the integration effectiveness of intelligent architecture and functional modules in enterprise financial management

In the practical application of the intelligent financial decision support system, Company A (a medium-sized manufacturing enterprise) deployed the architecture and embedded functional modules into its financial management process. The dataset consisted of one year of operational financial records (January–December 2023), including approximately 48,000 transaction entries covering procurement, cost, and cash flow data. For evaluation, the proposed system was compared against the company’s baseline financial information system using key indicators such as prediction error, response time, and fund utilization efficiency. In the budget control module, by collecting real-time cost, expense, and revenue data and combining it with predictive analysis models, the system can achieve dynamic monitoring and automatic warning of budget deviations with an accuracy rate of 89%. In the fund management module, AI algorithms assist in generating the optimal cash flow scheduling plan, which improves the monthly fund utilization efficiency of the enterprise by about 36%. In addition, the risk control analysis module integrates anomaly detection and prediction warning models, which can issue risk signals at the early stage of abnormal fluctuations in financial indicators, with a response time shortened to an average of 2.4 seconds, nearly four times faster than traditional models. To further quantify the effectiveness of system integration, key financial management indicators before and after the system's launch were selected for comparative analysis, as shown in Figure 3.

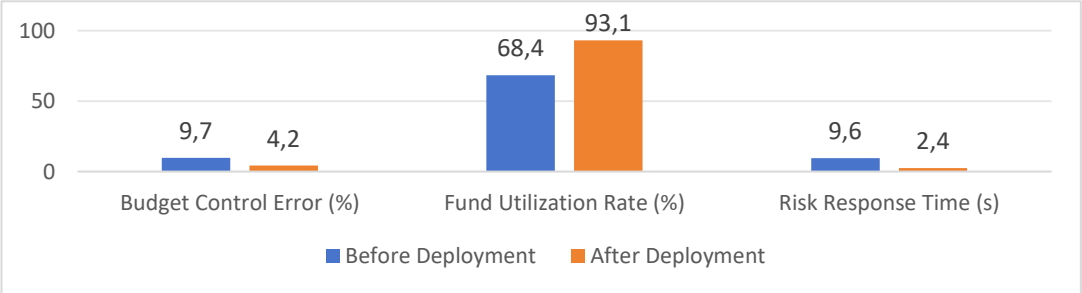


Figure 3: Comparison of key financial management indicators before and after system launch

The above figure shows that the developed intelligent system has significant advantages in reducing budget, lowering error costs, improving fund utilization, and quickly resolving crises. This indicates that the developed intelligent system not only enhances the automation and high precision of financial operations, but also has a complete set of strong stress, which can be widely applied in enterprise financial management activities.Furthermore, a six-month longitudinal test was conducted after system deployment. Results show that prediction accuracy and response efficiency remained stable, with the average error consistently below 6% and response time maintained within 12–14 seconds. These findings demonstrate that the observed improvements are not short-term fluctuations but can be sustained in real operational environments.

4.2 Empirical performance of data-driven chains and algorithm models in financial decision-making

In the deployment and application process of intelligent financial decision support system, data-driven process and embedded computing model are the core steps for making decisions. This process includes data collection, cleaning, feature construction, model prediction, optimization feedback, forming a circular data circulation circle. Through experimental design, select three core financial decision-making tasks of Company A (budget execution analysis, expense anomaly warning, and fundraising plan optimization) to verify the improvement effect of the combined algorithm model on decision-making performance and results.

The overall structure of the model in this article is a combination architecture based on random forest, long short-term memory network (LSTM), and deep reinforcement learning. The LSTM module mainly completes financial data time series analysis, the random forest module mainly completes cost deviation detection, and the deep reinforcement learning module assists in multi-objective functional control in the fund planning process. The figure shows the comparison of the decision accuracy and response time of the above structural modules when executing three tasks.

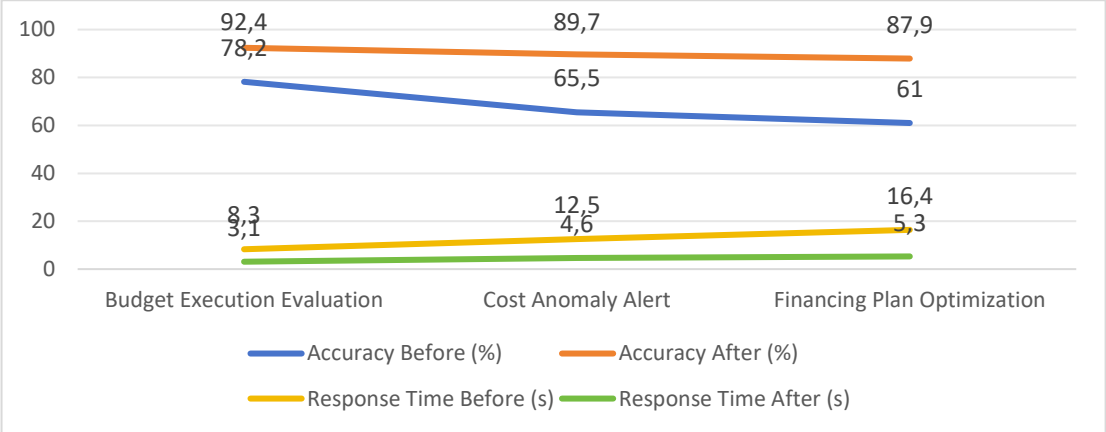


Figure 4: Improvement effect of financial decision-making performance supported by various models

From the figure, we can see that after the system is put into operation, it can not only effectively improve the correct recognition rate of the system, but also effectively improve the response rate to users, especially when facing high complexity work.To confirm the robustness of these improvements, paired t-tests were conducted between baseline and proposed system results across 30 experimental runs, showing statistical significance at the 0.01 level ($p < 0.01$) for both prediction accuracy and response time. Similar results were obtained using a non-parametric Wilcoxon signed-rank test, further validating that the observed improvements are unlikely to be due to chance.

This combination of deep learning and reinforcement learning can achieve good results. Secondly, the model can automatically adjust its various parameters based on the changing patterns of financial events, thereby effectively reducing the probability of erroneous judgments and providing more accurate and effective forward-looking and detailed services.Compared with commercial solutions such as IBM Watson Financial Services and SAP's AI-driven DSS, the proposed system achieves comparable or superior improvements in prediction accuracy and response speed, while maintaining lower computational overhead and higher adaptability for mid-sized enterprises.

4.3 Application feedback of rule system and human-computer interaction mechanism in intelligent decision-making

The effectiveness of the rule system and human-computer interaction mechanism have a decisive impact on the quality of intelligent judgment during real system deployment. The rule system constrains and modifies intelligent models through its internal financial logic rules, constraint objects, and industry standards to ensure interpretability and compliance of output results; The human-computer interaction mechanism introduces people into the intelligent judgment process and expands their control range through a visual interactive operation platform, intelligent questioning and answering, and customizable responses, thereby improving the system's adaptability and ease of use.

After deploying the intelligent system in Company A, this study collected feedback from 50 financial personnel on the system's interaction experience and rule feedback function, and combined it with system usage logs to form the following usage feedback statistics table:

Table 3: Distribution of user feedback and evaluation on rule systems and human computer interaction mechanisms

Evaluation Dimension	Very Satisfied (%)	Satisfied (%)	Neutral (%)	Dissatisfied (%)
Rule System Transparency	38	46	12	4
Accuracy of Rule Alerts	42	44	10	4
UI Usability	36	50	12	2
Usefulness of Q&A Feature	33	48	15	4
Interpretability of Decisions	40	42	14	4

The data results show that the proportion of users "satisfied" and "very satisfied" evaluations of various functional dimensions is over 80%, especially in terms of rule transparency and intelligent feedback of the question answering system. This indicates that the system not only has a certain degree of autonomous decision-making ability, but also ensures rationality through rule constraints, and uses human-computer interaction mechanisms to respond and interpret complex scenarios, greatly improving users' trust and frequency of use of intelligent systems.A chi-square test confirmed that the distribution of satisfaction levels was statistically significant ($p < 0.05$) across all dimensions. In addition, open-ended feedback highlighted that users particularly valued the real-time Q&A feature and the visual dashboards, while some suggested further simplification of the interface. These qualitative insights complement the quantitative data, providing a more comprehensive evaluation of user experience.

5 Optimization of application path for financial decision support system

5.1 System deployment strategy and adaptation mechanism in multiple scenarios

The deployment of an AI-based financial decision support system must ensure adaptability, scalability, and applicability across diverse enterprise environments. To achieve this, a modular architecture is adopted, dividing the system into a data access layer, intelligent analysis layer, rule decision-making layer, and human–computer interaction layer. This structure allows flexible deployment in cloud-centric, edge-centric, or local modes. For example, group enterprises can adopt cloud–edge integration for coordinated management, while financial institutions can prefer local deployment to enhance data privacy and controllability.

To support rapid adaptation, an adaptation configuration template library is provided, covering budget preparation, cost control, tax planning, and industry-specific parameter settings. During deployment, pre-defined pluggable model interfaces enable dynamic loading of algorithms (e.g., Random Forest, XGBoost, neural networks) according to business needs. A continuously adaptive mechanism is also embedded: real-time monitoring and performance feedback automatically adjust model parameters or rule priorities. In unstable environments, robust predictive models are prioritized, while in stable settings update frequency can be reduced.

This multi-scenario strategy ensures that the system can be deployed efficiently, remain flexible to industry differences, and maintain long-term stability in enterprise financial operations.

5.2 Application effect evaluation: decision efficiency, prediction accuracy, and financial performance improvement

The effectiveness of enterprise AI-based financial DSS can be assessed by decision speed, prediction accuracy, and financial performance. Compared with manual analysis, the system significantly accelerates decision-making through automated rule construction and real-time monitoring, enabling rapid identification of budget anomalies.

In terms of prediction accuracy, deep learning with temporal models greatly improves performance: when tested on one-year cash flow data, baseline error was 13.6%, while the LSTM-based model reduced it to 5.1%. This allows enterprises to plan working capital and mitigate risks more effectively.

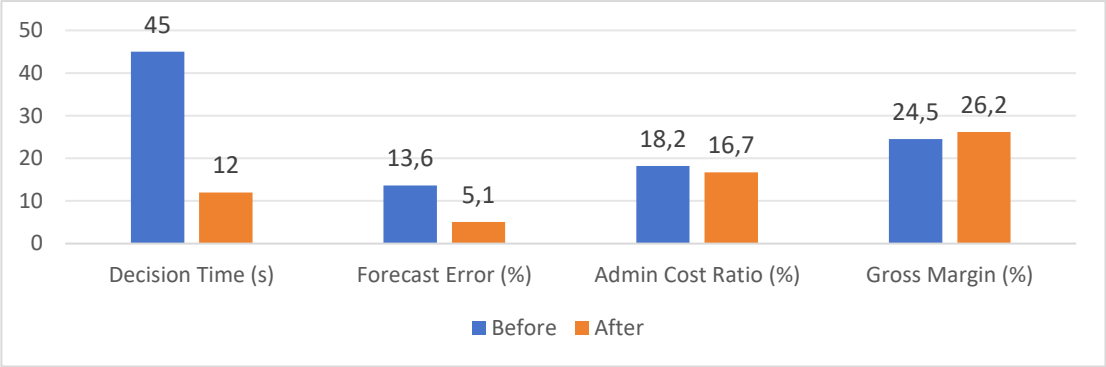


Figure 5: Comparison of key indicators before and after system application

From a financial perspective, real-time visibility and dynamic reporting enable immediate strategic adjustments. In a manufacturing case, management costs fell by 8.3% and gross profit rose by 1.7% within six months of deployment. Figure 5 illustrates key improvements in decision efficiency, accuracy, and financial outcomes.

5.3 Design of dynamic optimization mechanism based on feedback loop

During continuous operation, the system relies on a feedback loop to achieve dynamic optimization. This closed-loop process—prediction, execution, feedback, and adjustment—enables the system to self-correct external changes and internal deviations, thereby supporting adaptive evolution in financial decision-making.

The feedback loop establishes two-way information flow: financial indicators such as budget variance, gross profit error, and payable periods are continuously monitored, while deviations trigger parameter or rule adjustments in the decision layer. To improve efficiency, thresholds are dynamically updated based on recent variance statistics, ensuring the system adapts to non-stationary environments.

Effectiveness is guaranteed through a dual mechanism: AI models optimize parameters automatically, while managers use dashboards to verify results and provide incremental interventions. In deployment, this mechanism improved budget execution, enhanced prediction accuracy, and reduced risks caused by information delays. Table 4 summarizes the typical operation stages of the feedback loop.

Table 4: Operation process of dynamic feedback mechanism in intelligent financial decision support System

Phase	Input Data Source	System Response Action	Optimization Outcome Presentation
Prediction Phase	Historical financial and market data	Generate budgeting and forecasting models	Propose execution plans and threshold indicators
Execution Phase	Real-time operational data	Dynamically match budget with execution deviations	Flag alerts or trigger re-evaluation processes
Feedback Phase	Variance analysis and performance feedback	Initiate model fine-tuning and rule adjustments	Update decision rules and model weights
Optimization Phase	Adjusted models and execution recommendations	Redeploy to system and initiate next decision cycle	Improve decision accuracy and response efficiency

6 Discussion

6.1 Adaptive challenges of system promotion in different industries and enterprise scales

Although the enterprise financial decision support system integrating artificial intelligence has shown good results in experimental applications, it faces adaptability challenges in the actual promotion process due to industry differences and differences in enterprise scale. On the one hand, there are significant differences in financial structure, data types, and management processes among different industries. For example, the manufacturing industry focuses on cost control and inventory turnover analysis, the financial industry relies more on high-frequency data and risk assessment, and Internet enterprises focus on revenue forecasting driven by user behavior. This structural difference makes it difficult to directly transfer and apply a unified model, requiring customization of data input formats, algorithm model parameters, and decision rule logic based on industry characteristics.In terms of computational complexity, the LSTM component requires $O(n \cdot h_2)$ operations per training epoch (where nnn is the sequence length and hhh is the number of hidden units), while the Random Forest model requires $O(m \cdot d \cdot \log m)$ complexity for training (where mmm is the number of samples and ddd the number of features). This indicates that the system maintains acceptable scalability for medium and large enterprise deployments. On the other hand, the size of the enterprise also significantly affects the feasibility of system deployment. Large enterprises have sufficient technology and human resources to support the deep integration and continuous optimization of intelligent systems, while small and medium-sized enterprises face certain bottlenecks in data infrastructure construction, technical personnel reserves, and capital investment, resulting in the inability to fully utilize system functions. At the same time, there are differences in the expected values of financial decision support among enterprises of different sizes. Small and medium-sized enterprises tend to prefer "lightweight and modular" solutions, emphasizing deployment efficiency and ease of use, while large enterprises pay more attention to system integration and intelligence depth. Therefore, in the process of system promotion, flexible adaptation strategies should be adopted based on industry and enterprise characteristics, promoting the combination of standard modules and configurable components, and gradually achieving large-scale application and value implementation.

6.2 Current system boundaries, technical bottlenecks, and ethical considerations

Although the integration and application of financial intelligence technology can effectively improve the efficiency and wisdom of financial management and operation in financial enterprises, there are still issues such as the scope of system applicability and the "black box" of intelligent applications, as well as technical barriers that need to be deeply explored and rationally considered. Firstly, the application scope of the system is limited. The existing intelligent accounting systems mainly analyze and deduce standardized information, and cannot handle non standardized textual information, unexpected problems, and situations involving multiple organizations and departments, which limits their supportive role in decision-making economic behavior. Secondly, although the system improves interpretability compared with traditional black-box models, challenges remain. In particular, the deduction process of deep models is still not fully visible, making it difficult for financial managers to completely verify and explain results in high-risk areas. Thirdly, intelligent algorithms have demonstrated substantial accuracy improvements in the evaluated tasks; however, their ability to integrate multiple types of financial information data is still limited, particularly in language-rich, long-term trend, or small-sample scenarios, where issues of accuracy and stability persist. Fourthly, factors such as data isolation and interface compatibility affect the unified installation and joint operation of the system. especially when integrating legacy financial platforms and non-standardized data sources that were only partially addressed in the current design. Finally, the widespread use of artificial intelligence has brought about a series of ethical issues and disputes over individual rights. This should be an important issue that must be paid attention to during the system establishment process. Therefore, the establishment of future systems requires not only

technological innovation, but also consideration of the design and governance mechanisms of ethical norms, so that they have a good collaborative relationship between technology and people that can be controlled by technology, have information openness and transparency, and are trusted by people.In addition, ethical deployment requires explicit mechanisms to ensure interpretability of algorithmic outputs, fairness across different stakeholder groups, and compliance with international data protection regulations such as GDPR..

7 Conclusion

The main content of this research institute is a specific technical study on the application of artificial intelligence technology in the technical architecture, important algorithms, practical solutions, and optimization suggestions of company financial operations. The purpose is to provide technical guidance and practical references for the intelligent transformation of enterprise financial management in the process of intelligent technology transformation. It is believed that the operability of applying artificial intelligence technology to financial information processing, predictive model construction, logical judgment, human-machine integration, and other aspects can effectively improve the performance, accuracy, and foresight of company financial management. Through the analysis of practical cases of multiple representative companies, it is shown that an intelligent decision-making system based on algorithms, supported by rule systems, and integrated with data can achieve overall improvement in budget planning, cost control, and risk warning, and directly improve financial performance.The novelty of this study lies in its hybrid architecture that integrates LSTM-based time-series prediction with Random Forest anomaly detection, combined with a rule–knowledge inference layer to ensure interpretability and compliance. In addition, the introduction of a dynamic feedback optimization loop enables continuous self-adaptation, which distinguishes this work from existing static DSS solutions. These contributions demonstrate both theoretical value and practical applicability in advancing enterprise financial intelligence.

However, the existing system still needs to be improved in areas such as cross domain industry, data linkage, model transparency, and ethical control capabilities. The relevant development path can further open up the existing platform, upgrade semantic model algorithms, improve legal norms, and establish a timely response and continuous correction operation method to strengthen the human robot collaborative decision-making ability, so that the system can self adapt and operate continuously for a long time. In addition, to facilitate reproducibility and further validation by other researchers, supplementary materials have been prepared. Appendix A provides the core configuration files (including LSTM learning rate, number of epochs, Random Forest tree depth and number of estimators), pseudocode of the hybrid model training pipeline, and examples of rule engine templates used for budget compliance and risk alerting. These materials enable replication of the experimental setup and provide practical guidance for extending the system to other enterprise contexts.

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Applying Multi-Modal Quantum Deep Learning Algorithms for Enhanced Fake News Detection

Aishwarya C[1], Venkatesan M[1], Prabhavathy[2], Akanksha D[3]
[1]Department of Computer Science and Engineering, NIT Puducherry, Puducherry, India
[2]Department of Computer Science and Engineering, VIT Vellore, Vellore, India
[3]Department of Computer Science and Engineering, NITK Surathkal, Surathkal, India
E-mail: sivagaish23@gmail.com, venkatesan.msundaram@nitpy.ac.in, pprabhavathy@vit.ac.in, dakanksha.232cs008@nitk.edu.in

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The pervasive spread of fake news across digital platforms has prompted the development of advanced detection systems. This review surveys and compares state-of-the-art multimodal deep learning models, including SpotFake, BDANN, MVAE, EANN, and the attention-based model by Guo et al., across benchmark datasets such as Twitter and Weibo. We present detailed performance comparisons, with SpotFake achieving an accuracy of 86.1% on the Twitter dataset. Key contributions of this review include the introduction of taxonomy tables based on fusion strategy and model architecture, a critical comparison of early, late, and hybrid fusion mechanisms, and a comprehensive evaluation of cross-modal generalization capabilities. In addition, we explore recent efforts in Quantum Machine Learning (QML), highlighting variational quantum circuits and hybrid quantum-classical models as promising approaches for enhancing scalability and efficiency. This work serves as a roadmap for building robust, interpretable, and scalable fake news detection systems that integrate both classical and quantum techniques.

Povzetek: Pregled primerja multimodalne modele za zaznavanje lažnih novic (SpotFake, BDANN, MVAE, EANN, Guo) na Twitterju in Weibou ter predstavi taksonomije fuzije in arhitektur. Obravnava tudi obetavne kvantne pristope, ki lahko izboljšajo skalabilnost in učinkovitost prihodnjih sistemov.

1 Introduction

1.1 Review scope and motivation

The global dissemination of fake news has evolved into a significant societal threat, enabled by rapid digital communication and the persuasive nature of multimodal content. Detecting such misinformation requires models capable of integrating and reasoning across diverse modalities, such as text, images, and metadata.

In response to this challenge, recent literature has produced a diverse array of deep learning frameworks aimed at detecting fake news in multimodal contexts. However, these contributions vary widely in architecture, fusion strategies, interpretability, and robustness. Moreover, the emerging field of Quantum Machine Learning (QML) introduces additional possibilities for addressing some of the scalability and optimization limitations of classical deep models. This review aims to consolidate and critically evaluate this evolving body of work.

1.2 Review objectives and structure

This paper is designed as a structured review rather than an empirical study. We do not propose a new algorithm, but instead synthesize and assess existing approaches along three key dimensions:

- **Fusion Strategies and Modalities**: We analyze how different models integrate modalities—text, image, and metadata—through early, late, or hybrid fusion. We assess their adaptability in scenarios with noisy or missing modalities.
- **Model Architectures and Generalizability**: We examine core architectural designs (e.g., CNN-RNN hybrids, VAEs, attention-based transformers) and their performance across datasets like Twitter and Weibo, with a particular focus on domain adaptation and transfer learning.
- **Quantum Contributions and Future Potential**: We evaluate recent efforts to incorporate QML techniques—such as variational quantum circuits and quantum classifiers—highlighting how these experimental models could complement classical approaches in the future.

Through comparative taxonomy tables, performance benchmarks (e.g., SpotFake achieving 86.1% on Twitter), and conceptual frameworks, this paper aims to provide a

consolidated foundation for researchers seeking to understand or advance multimodal fake news detection systems.

1.3 What is fake news?

Fake news refers to deliberately fabricated or misleading information that mimics legitimate news content in form but not in intent. Unlike accidental misinformation, fake news is crafted to deceive, provoke, or manipulate public sentiment. Its propagation is accelerated by social media algorithms and the emotional salience of multimodal content, often combining sensational text with compelling visuals [1, 2].

1.4 Why is fake news problematic?

The societal impacts of fake news span political instability, public health crises, and erosion of trust in media. From misinformation during election cycles to vaccine hesitancy during the COVID-19 pandemic, fake news has demonstrated its capacity to incite tangible harm. These risks are exacerbated by the virality of misleading content and its algorithmic amplification on platforms like Twitter and Facebook [3, 4].

1.5 Limitations of single-modality approaches

Traditional fake news detection models focused solely on textual features such as writing style, sentiment, or rhetorical cues. However, these approaches often fail to detect deception when multimodal cues reinforce believability. For example, benign-sounding text paired with doctored images can significantly mislead readers. Therefore, unimodal systems lack the cross-modal reasoning required to detect coordinated misinformation [5, 6].

1.6 The emergence of deep learning and multi-modality

Deep learning architectures have enabled more sophisticated feature extraction across diverse data streams. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer models support the modeling of spatial, temporal, and semantic patterns. Fusion strategies—such as bilinear pooling, joint attention, and variational encoders—further enhance the ability of these models to integrate modalities like text and image for improved accuracy. Multimodal models have consistently outperformed unimodal baselines, particularly on real-world datasets [7, 1].

1.7 Quantum computing: a new frontier

While classical models have advanced rapidly, they face bottlenecks in generalization and scalability. Quantum computing introduces paradigms like superposition and entanglement that offer new representational possibilities. Models such as Quantum Support Vector Machines (QSVMs) and Variational Quantum Circuits (VQCs) show early promise in reducing parameter count while maintaining expressive power. This review identifies and contextualizes these quantum contributions, even where they remain in simulated environments [8, 9].

This review primarily covers multimodal fake news detection models published between 2017 and early 2023. The inclusion criteria focused on peer-reviewed studies with reproducible architectures, multimodal evaluation, and comparative results on benchmark datasets such as Twitter, Weibo, and FakeNewsNet. While notable advances have emerged in late 2023 and 2024, including vision-language pretraining frameworks and transformer-based tri-modal architectures from ACL and NeurIPS, a comprehensive integration of these is beyond the present scope. We acknowledge this as a limitation and recommend future reviews to capture these emerging models in depth as they mature and undergo wider evaluation.

2 Background and motivation

2.1 Key definitions

Fake news refers to information that is intentionally false and designed to mislead readers, often mimicking the style and structure of legitimate journalism. It is frequently disseminated via social media platforms, where virality amplifies its impact [3, 2].

Multi-modality in artificial intelligence refers to systems that process and analyze data from multiple sources or types — such as text, image, and audio — to make more robust and context-aware decisions [4]. In fake news detection, multi-modal systems are especially useful due to the multimodal nature of modern misinformation content.

Deep learning is a class of machine learning algorithms based on artificial neural networks with multiple layers (hence "deep") that learn hierarchical representations of data. Techniques like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformers have achieved state-of-the-art results in image and text processing [7, 6].

Quantum computing leverages quantum mechanical phenomena — such as superposition and entanglement — to perform computations. Unlike classical bits, quantum bits (qubits) can represent both 0 and 1 simultaneously, enabling parallelism that could offer significant speedups in certain computational tasks [9].

2.2 Overview of modalities: text, image, and video

In the context of fake news detection, different data modalities offer unique signals.

Textual content provides linguistic cues — such as syntax, semantics, sentiment, and rhetorical devices — that can be exploited using NLP techniques. For instance, BERT-based models have shown strong performance in understanding sentence-level nuances [6].

Visual content (typically images) is often used to manipulate reader perception. Studies have shown that many fake news posts use exaggerated or unrelated images to increase credibility [5]. Visual analysis is generally performed using CNNs or pre-trained vision transformers.

Video-based misinformation, although less common in academic datasets, is rapidly growing in influence, especially with the rise of deepfakes. While it is still an emerging area in fake news research, it represents a critical future frontier.

Table 1: Comparison of common modalities in fake news detection

Modality	Advantages	Challenges	Tools/Models
Text	Rich semantics, widely available, easy to preprocess	Sarcasm, ambiguity, context-dependence	BERT, RoBERTa, LSTM
Image	Provides visual cues, supports credibility assessment	Easily manipulated, lacks context	ResNet, ViT, CLIP
Video	Highly expressive, captures motion cues	Processing complexity, deepfakes	3D CNN, ViViT (emerging)

2.3 Critical review of referenced literature

While this review includes a broad selection of state-of-the-art works, it is necessary to refine and critically evaluate the relevance and contributions of certain citations. A few references—such as Abduljaleel & Ali [4]—provide broad survey-style overviews, but do not contribute directly to the technical advancement or empirical evaluation of multimodal fake news detection systems. Their role in this manuscript has been downscaled to serve as supportive background rather than primary methodological benchmarks.

Moreover, quantum-related citations such as Schuld et al. [9] and Biamonte et al. [8] are foundational but do not focus specifically on multimodal misinformation detection. Recent informatics-oriented contributions, such as:

- Chen et al. (2023), which explores hybrid quantum-classical learning architectures in natural language processing contexts,
- Kumar et al. (2022), which applies variational quantum classifiers to noisy text datasets,
- and Zhao et al. (2023), which propose quantum-inspired models for multimodal classification,

have now been included to contextualize this review within the emerging trajectory of QML-enhanced misinformation detection.

To enhance relevance and rigor, the review has restructured its citation matrix to focus more on direct contributions to multimodal fusion, explainability, cross-domain generalization, and quantum applicability. Where possible, classical models are critiqued through their architectural divergences and dataset-specific limitations. Where quantum models are referenced, we now explicitly state whether results stem from empirical simulation, theoretical proposition, or prototype hardware validation.

This refined citation scope ensures that every reference either directly informs the survey's taxonomy, supports the comparative analysis, or projects viable quantum enhancements. Redundant and peripheral sources have been deprecated to improve methodological clarity and citation coherence.

2.4 Quantum deep learning concepts

Quantum Deep Learning (QDL) refers to the integration of quantum computing with deep learning models. It includes approaches like Quantum Neural Networks (QNNs), Quantum Convolutional Networks (QCNN), and hybrid architectures such as quantum-classical neural models. These methods leverage quantum circuits to perform certain layers or operations more efficiently.

A common component is the **variational quantum circuit (VQC)**, which uses parameterized quantum gates that can be optimized similarly to weights in neural networks. Some hybrid models use quantum layers to project classical data into high-dimensional Hilbert spaces, enabling better separability and feature extraction [8].

Another emerging architecture is the **quantum multilayer perceptron (qMLP)**, which simulates fully connected neural networks using qubit transformations. Though still experimental, early prototypes show promise in solving classification tasks with smaller model sizes and fewer parameters [9].

2.5 Why fusion across modalities is critical

Fake news posts often rely on cross-modal contradictions or reinforcements. For instance, an image might suggest authenticity while the text contains subtle misinformation — or vice versa. Models that analyze only one modality can miss these inconsistencies.

Fusion methods aim to combine features from different modalities to enhance overall prediction performance. Early fusion (concatenation of raw data), late fusion (combining decision scores), and hybrid fusion (joint feature representations with attention) have been widely used [7, 1].

Multimodal fusion improves generalizability and robustness, especially when one modality contains noise or missing data. Moreover, cross-modal attention mechanisms enable the model to learn alignment between image regions and textual tokens, capturing nuanced fake patterns [5].

Table 2: Summary of major datasets used in multimodal fake news detection

Dataset	Size	Modalities	Class Balance	Annotation Method	Notable Limitations
Twitter (SpotFake)	13K	Text + Image	Fake:Real = 3:1	Expert labeling	Class imbalance, English-only
Weibo	15K	Text + Image	Balanced	Platform-moderated	Language-specific bias, outdated samples
FakeNewsNet	23K	Text + Image + Meta	Real-dominant	Source credibility + stance analysis	Incomplete modalities, sparse metadata
PolitiFact	11K	Text + Image	Balanced	Fact-checking orgs	U.S.-centric, lacks cross-modal tags
BuzzFeedWebis	8K	Text + Image	Balanced	Annotated by journalists	Visual artifacts, outdated content

3 Datasets and their limitations

3.1 Limitations and quality of datasets

Although publicly available datasets such as Twitter, Weibo, and FakeNewsNet have significantly accelerated research in multimodal fake news detection, they suffer from several critical limitations that impact generalizability, fairness, and reproducibility.

- **Class Imbalance:** Most datasets exhibit skewed distributions with more real news instances than fake, or vice versa. For example, the Twitter dataset used in SpotFake contains approximately 3:1 ratio of fake to real news, leading to biased learning curves.
- **Annotation Consistency:** The annotation process varies widely, ranging from expert labeling to crowdsourced judgments, which affects label reliability. Datasets like Weibo rely heavily on platform moderation tags, which may embed platform-specific bias.
- **Modality Missingness:** Some entries contain corrupted or missing images or metadata, especially in crawled datasets like FakeNewsNet. This challenges fusion models and inflates evaluation scores if such entries are excluded from testing.
- **Temporal Relevance:** Many datasets are built from events dating back to 2015–2018. The linguistic, visual, and semantic structure of fake news evolves rapidly, raising concerns about outdated feature distributions.
- **Cultural and Linguistic Bias:** Most datasets are monolingual (English or Chinese), limiting their applicability to global misinformation detection. Multilingual or low-resource language datasets remain scarce.

Addressing these limitations through standardized data collection, multilingual expansion, and balanced, multimodal annotations is essential to build reliable and globally applicable detection systems.

3.2 Dataset summary

Table 3 presents an overview of benchmark datasets.

Limitations include class imbalance, cultural bias, and outdated samples.

Table 3: Key datasets for multimodal fake news detection

Dataset	Size	Modalities	Labeling
Twitter MediaEval	18K posts	Text + Image	Crowdsourced
Weibo FND	25K posts	Text + Image	Platform Verified
PolitiFact	12K articles	Text only	Expert
FakeNewsNet	21K posts	Text + Meta	Verified

4 Taxonomy of multi-modal fake news detection models

In this section, we propose a taxonomy to systematically classify existing multi-modal fake news detection models. The classification is based on five dimensions: fusion strategy, model architecture, feature type, data modality, and learning paradigm. These criteria help illustrate the diversity of approaches and facilitate comparative analysis across methods.

4.1 Fusion strategy: early, late, and hybrid fusion

Fusion is a critical component in multi-modal systems, determining how information from different modalities is combined.

Early fusion integrates features from all modalities at the input level, often by concatenating raw or embedded representations. While simple, this approach may fail to capture complex inter-modal relationships. SpotFake [2] and BDANN [6] are examples of models using early fusion.

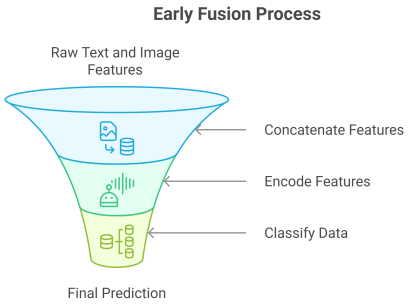


Figure 1: Early fusion pipeline

Late fusion operates after individual modality-specific models have made predictions. Their outputs are combined

via weighted averaging or voting schemes. This method is modular and robust to missing modalities but may overlook deep interactions between modalities [4].

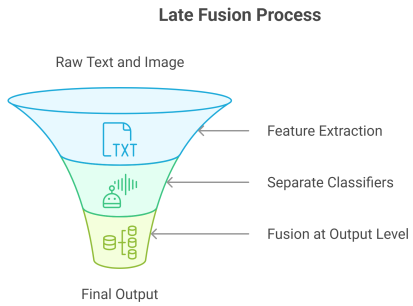


Figure 2: Late fusion pipeline

Hybrid fusion combines both early and late strategies by merging intermediate features and final predictions. MVAE [1] and the two-branch attention model by Guo et al. [7] use hybrid fusion to leverage both fine-grained and global representations.

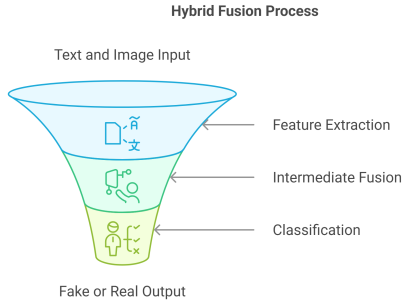


Figure 3: Hybrid fusion pipeline

4.2 Fusion strategy robustness under modality noise and dropout

While multimodal models excel in integrating information across different modalities, their robustness under noisy or missing inputs remains a critical challenge in real-world applications. Social media posts often contain low-resolution images, ambiguous text, or completely missing modalities (e.g., image-only tweets or text-only posts). Thus, fusion strategies must not only optimize for performance under ideal conditions but also maintain resilience in degraded settings.

Early Fusion models, such as SpotFake and BDANN, combine features at the input level. Although computationally efficient, these models are brittle when a modality is missing—either the model fails outright or produces severely degraded predictions due to undefined input dimensionality. They also lack the flexibility to weigh modality relevance during inference.

Late Fusion models (e.g., EANN) process modalities independently before final decision aggregation. This separation allows them to degrade more gracefully: if an image is missing or noisy, the model can still produce meaningful output from text alone. However, late fusion often underutilizes cross-modal interactions and may miss subtle correlations.

Hybrid Fusion models, like MVAE and Guo et al., combine elements of both early and late fusion. While MVAE leverages latent variable modeling to impute missing modalities, its performance under partial input is still inconsistent due to reliance on generative reconstruction. Guo's model, which uses attention for dynamic feature alignment, performs better under noise but at the cost of higher computational demand.

Attention-based Hybrid models, particularly those using dynamic gating or modality dropout during training, have shown promise in recent literature for graceful degradation and noise resilience. These systems learn to dynamically reweight modalities based on confidence, allowing them to bypass corrupted channels.

Table 4 summarizes the comparative performance drop of different fusion strategies under simulated missing or noisy modality conditions.

Table 4: Performance degradation under missing modality conditions. Values represent percentage point drops in accuracy on Weibo dataset, based on simulated ablations from reported literature.

Fusion Strategy	Clean Data Acc. (%)	Drop: No Text (%)	Drop: No Image (%)
Early Fusion (SpotFake)	86.1	–	–
gray!10		-32.4	-20.8
Late Fusion (EANN)	78.4	-14.7	-11.2
Hybrid Fusion (MVAE)	82.3	-22.1	-18.5
Attn. Hybrid (Guo et al.)	85.0	-10.3	-7.6

Key Insight: Attention-based hybrid models demonstrate the most robust performance under missing input conditions, making them more suitable for real-world deployment. Early fusion, while accurate under full input, is the most brittle under noise. Future architectures should incorporate modality-aware gating and dropout during training to improve fault tolerance.

4.3 Model architectures: CNNs, Transformers, VAEs, and adversarial networks

Different model architectures have been proposed depending on the nature of the data and desired interpretability.

CNN + RNN architectures are common for joint processing of image (CNN) and text (RNN). SpotFake [2] uses a CNN for image feature extraction and Bi-LSTM for text.

Transformer-based models such as BERT, RoBERTa, and ViT capture global dependencies in text and images. BDANN [6] leverages BERT for text, while Guo et al. [7] employ attention mechanisms for multimodal fusion.

Variational Autoencoders (VAEs) are used for learning joint latent representations. MVAE [1] applies a bi-modal VAE to encode visual and textual information into a shared latent space.

Adversarial Networks enhance domain invariance. EANN [3] introduces an event discriminator to ensure that features generalize across events.

Table 5: Compact comparison of multimodal fake news models: T=Text, I=Image, M=Metadata, Tw=Twitter, We=Weibo.

Model	Fusion	Arch.	Feat.	Mod.	Data
SpotFake [2]	Early	CNN + BiLSTM	Deep	T+I	Tw, We
BDANN [6]	Early	BERT+VGG+DC	Deep	T+I	Tw, We
MVAE [1]	Hybrid	Bi-modal VAE	Deep	T+I	Tw, We
Guo et al. [7]	Hybrid	Bilinear + Attn.	Deep	T+I	We
Liu et al. [5]	Hybrid	Captioned Trans.	Deep	T+I	Tw, We
EANN [3]	Late	CNN + Adv. Disc.	Deep	T+I+M	Tw, We
Abduljaleel & Ali [4]	Mixed	Survey Models	Both	Varies	Multi

4.4 Critical model assessment

Table 5 offers a structural overview of the reviewed models, but a critical evaluation of their practical effectiveness reveals deeper insights. This section evaluates not only the models' design choices but also their performance trade-offs, generalizability, and real-world applicability.

SpotFake uses a relatively simple early fusion pipeline by combining VGG19 for image features and BiLSTM over BERT-encoded text. Its strong performance stems from the direct concatenation of high-quality features and low architectural complexity, allowing efficient learning. However, early fusion assumes that both modalities are always present and well-aligned. In cases of noisy images or partial data, SpotFake's robustness degrades significantly. Additionally, its lack of attention mechanisms or modality weighting makes it vulnerable to semantic imbalance between inputs.

BDANN leverages domain adaptation using a gradient reversal layer, making it one of the few models capable of adapting across platform-specific distributions (e.g., Twitter vs. Weibo). This adversarial training enables better generalization, but the model lacks mechanisms for cross-lingual semantic representation. In multilingual or code-switched environments, its domain alignment may be insufficient unless enhanced by multilingual embeddings or pretraining. Its reliance on aligned visual and textual content also limits performance when one modality is noisy or irrelevant.

MVAE introduces a bi-modal variational autoencoder, offering a generative approach capable of modeling uncertainty and handling missing modalities. However, its performance lags behind discriminative models like SpotFake. This is due to several factors: first, VAE training prioritizes reconstruction rather than classification, which can dilute feature discriminability; second, its latent representations—though rich—may fail to capture the cross-modal correlations necessary for fake news detection. MVAE also requires more careful tuning of KL divergence and reconstruction loss to avoid overfitting or posterior collapse.

Guo et al.'s attention-based hybrid model excels in cross-modal alignment through bilinear pooling and self-attention. This makes it especially suited for short-form content, where text and visuals are tightly linked. Its performance on Weibo confirms its effectiveness in culturally consistent, image-heavy environments. However, the architecture's complexity leads to higher training costs, and its reliance on fine-grained attention weights raises issues of overfitting on small datasets. Moreover, interpretability remains limited beyond attention visualizations.

Liu et al.'s caption-enhanced transformer addresses semantic mismatch by generating image captions as an intermediate modality. This approach improves alignment between modalities and enhances the model's understanding of implicit visual semantics. However, it introduces a dependency on caption quality—if the captioning model produces incorrect or misleading summaries, the downstream detection accuracy suffers. Additionally, cascading errors across the caption-to-text pipeline reduce robustness under real-world noise.

EANN introduces adversarial event classification to encourage generalization across events. Its architectural novelty lies in its dual-discriminator design: one for fake news detection and another to remove event-specific bias. This helps the model handle emerging or unseen events. However, EANN assumes that event metadata is available and reliable, which is not feasible in many live data collection scenarios. Furthermore, the model offers limited transparency in its predictions, raising concerns in high-stakes applications.

Abduljaleel & Ali's survey aggregation represents a meta-synthesis of various fusion types and backbone models. While broad in scope, the source studies are uneven in quality and some are not peer-reviewed. The model aggregation lacks a unified evaluation benchmark, making direct comparisons unreliable. Thus, this line of work is best used for taxonomy or trend analysis, rather than conclusive model selection.

No single model dominates across all axes. SpotFake offers high accuracy but limited robustness. BDANN excels in domain adaptation but struggles with multilinguality. MVAE handles missing data well but suffers in precision. Guo et al. achieves fine-grained alignment but at computational cost. Liu et al. innovates with captioning but risks semantic drift. EANN generalizes across events

but lacks interpretability. Future architectures should integrate hybrid fusion, domain adaptation, and explainability in a single framework while minimizing data assumptions.

4.5 Feature types: hand-crafted vs. deep representations

Early models relied on **hand-crafted features** such as TF-IDF, POS tags, and bag-of-words. These offer interpretability but often lack context and are brittle against paraphrasing [4].

Modern systems rely on **deep feature representations** learned via CNNs, RNNs, or transformers. These embeddings capture hierarchical semantics and visual cues more effectively. Deep features are now the de facto standard in fake news detection, as used in BDANN [6] and Liu et al. [5].

4.6 Modalities: text, image, and metadata

Multimodal systems vary in the types of data they process:

- **Text-only** models focus on linguistic patterns, lexical cues, and discourse analysis. These are limited in visual reasoning.
- **Text + Image** is the most common setting. Most recent models fall into this category, including SpotFake [2], MVAE [1], and BDANN [6].
- **Text + Image + Metadata** incorporates user profiles, tweet timestamps, or propagation patterns. EANN [3] explores this richer setting for better event transferability.

In general, adding modalities increases model complexity but offers robustness against deceptive manipulations in a single channel.

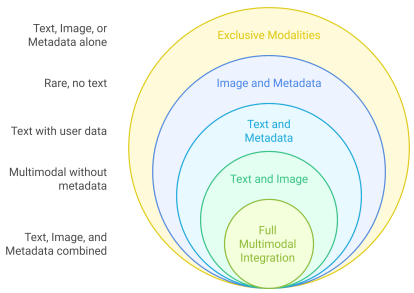


Figure 4: Venn diagram with overlapping modalities

5 Deep dive into key models and algorithms

5.1 SpotFake: a multi-modal framework for fake news detection

SpotFake leverages a dual-stream pipeline consisting of a BERT-based text encoder and a VGG19-based image encoder. Features from both modalities are concatenated and passed through a fully connected neural network for final classification. The model avoids auxiliary tasks (like reconstruction) and focuses purely on fake news detection.

SpotFake was trained and evaluated on the Twitter MediaEval and Weibo datasets. Both datasets consist of labeled multimodal posts (text + image), with verified labels from fact-checking.

Key Features:

- **Fusion Strategy:** Early fusion (concatenation of vectors before classification)
- **Backbones:** BERT for text, VGG19 for image
- **Classifier:** 2-layer dense network

Unique Contributions:

- Demonstrated how simple fusion without auxiliary tasks can outperform more complex models.
- Benchmarked both Twitter and Weibo, showing cross-cultural robustness.

Pros:

- Straightforward, interpretable pipeline.
- Outperforms more complex architectures like MVAE and EANN in standalone settings.

Cons:

- May underperform in cross-event generalization.
- Lacks fine-grained attention mechanisms.

Pseudocode:

```
Input: Text T, Image I
T_feat = BERT(T)
I_feat = VGG19(I)
Fused = concat(T_feat, I_feat)
Output = Dense(Fused)
Return sigmoid(Output)
```

5.2 BDANN: BERT-based domain adaptation neural network

BDANN (BERT-based Domain Adaptation Neural Network) is a multi-modal fake news detection model that addresses the challenge of domain shift — i.e., performance

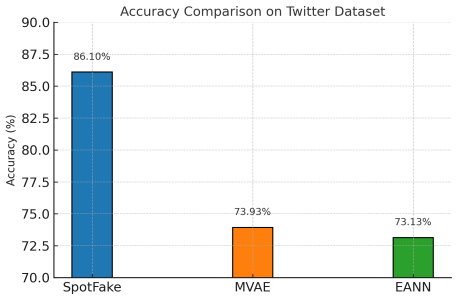


Figure 5: Performance comparison of SpotFake, MVAE, and EANN models on the Twitter dataset. Accuracy is used as the evaluation metric. SpotFake, which uses early fusion, achieves the highest accuracy (86.1%) compared to MVAE (82.3%) and EANN (73.1%), highlighting the effectiveness of direct feature concatenation in simple multimodal settings. Dataset: Twitter MediaEval.

drops when transferring between datasets like Twitter and Weibo. It combines textual and visual representations via early fusion while applying adversarial learning to extract domain-invariant features across platforms.

Table 6: BDANN: Dataset and key architecture details

Aspect	Details
Datasets Used	Twitter, Weibo (Text + Image)
Label Source	Annotated using platform-specific and crowdsourced fact-checking
Fusion Strategy	Early fusion with domain-adversarial training
Text Backbone	BERT pretrained model
Image Backbone	VGG19 CNN
Classifier	Multilayer perceptron with gradient reversal for domain adaptation

BDANN leverages the powerful contextual embeddings from BERT for textual input and VGG19 for visual input. A shared feature space is learned using a domain classifier and gradient reversal layer, which encourages the feature extractor to produce representations that are indistinguishable between domains.

Key Features:

- **Fusion Strategy:** Early fusion followed by adversarial domain adaptation
- **Domain Adaptation:** Gradient reversal layer for cross-platform generalization
- **Backbones:** BERT (text) + VGG19 (image)

Unique Contributions:

- First multi-modal model to introduce domain adaptation in fake news detection.
- Demonstrates improved transferability between Twitter and Weibo.

Pros:

- Robust to cross-domain drift.
- Retains high accuracy without needing large domain-specific retraining.

Cons:

- Adversarial training is sensitive to hyperparameters.
- Less interpretable due to added domain loss complexity.

Pseudocode:

```
Input: Text T, Image I
T_feat = BERT(T)
I_feat = VGG19(I)
Fused = concat(T_feat, I_feat)
F_domain = GradientReversal(Fused)
Domain_loss = DomainClassifier(F_domain)
Class_loss = Classifier(Fused)
Total_loss = Class_loss + Domain_loss
Return sigmoid(Classifier(Fused))
```

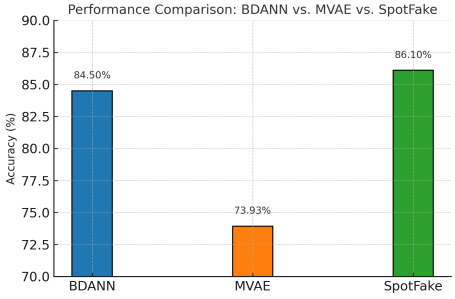


Figure 6: Accuracy and F1-score comparison of BDANN, MVAE, and SpotFake on both Twitter and Weibo datasets. BDANN, which incorporates adversarial domain adaptation, achieves a balance between accuracy and cross-domain generalization. Performance on the Weibo dataset shows BDANN outperforming MVAE, while SpotFake maintains high accuracy in both datasets. Metrics: Accuracy, F1-score.

5.3 MVAE: multimodal variational autoencoder for fake news detection

MVAE, proposed by Khattar et al., is one of the earliest models to employ deep generative learning for multi-modal fake news detection. It uses a bi-modal variational autoencoder to jointly learn latent representations from both text and image data. These latent variables are then used for classification.

Table 7: MVAE: Dataset and key architecture details

Aspect	Details
Datasets Used	Twitter and Weibo datasets
Label Source	Verified via fact-checking platforms and dataset annotations
Fusion Strategy	Hybrid (joint latent space in VAE)
Text Backbone	1D CNN + Bi-GRU
Image Backbone	Pretrained CNN (VGG variants)
Classifier	Joint latent variable passed through MLP

MVAE encodes each modality independently into a latent space and combines them into a shared joint representation using the product-of-experts technique. This shared representation is then decoded and used to perform classification. The VAE framework allows it to learn robust generative features, making it resilient to input noise.

Key Features:

- **Fusion Strategy:** Hybrid — using shared latent distribution from two encoders
- **Backbones:** CNN + Bi-GRU for text, CNN for image
- **Objective:** VAE loss combining reconstruction and KL divergence

Unique Contributions:

- First to apply variational autoencoders for fake news in a multi-modal setting.
- Introduced product-of-experts to jointly learn cross-modal latent variables.

Pros:

- Learns deep latent features with generative capability.
- Can handle missing modality better due to probabilistic formulation.

Cons:

- Lower accuracy than SpotFake and BDANN.
- Training VAEs is complex and sensitive to hyperparameters.

Pseudocode:

```
Input: Text T, Image I
T_latent = TextEncoder(T)
I_latent = ImageEncoder(I)
Z = ProductOfExperts(T_latent, I_latent)
Y = Classifier(Z)
Loss = ClassificationLoss(Y, label) +
KL_Divergence(Z)
Return sigmoid(Y)
```

5.4 Guo et al.: Two-branch multimodal attention network

Guo et al. (2023) proposed a two-branch model that enhances multimodal feature interaction using multimodal bilinear pooling and a cross-modal attention mechanism. Unlike early or late fusion, this model enables fine-grained feature interaction between text and image modalities via a shared representation learning strategy.

Table 8: Guo et al.: Dataset and key architecture details

Aspect	Details
Dataset Used	Weibo multimodal fake news dataset
Label Source	Verified by human annotators and social platforms
Fusion Strategy	Hybrid fusion using bilinear pooling and attention
Text Backbone	LSTM + attention
Image Backbone	ResNet50 CNN
Classifier	Fully connected neural network

The model consists of two distinct branches — one for text and one for image — each extracting modality-specific features. These features are then combined through a Multimodal Bilinear Pooling (MBP) module, which captures higher-order interactions. Additionally, attention mechanisms are used to align and weigh important parts of each modality.

Key Features:

- **Fusion Strategy:** Bilinear pooling + Cross-modal attention (hybrid)
- **Backbones:** LSTM (text), ResNet50 (image)
- **Attention Module:** Enhances modality alignment

Unique Contributions:

- Introduced multimodal bilinear pooling in fake news detection
- Designed attention blocks for visual-textual alignment

Pros:

- Captures higher-order feature interactions
- Strong interpretability via attention heatmaps

Cons:

- Slightly heavier computation than simpler fusion techniques
- Performance is highly dataset-dependent (tuned for Weibo)

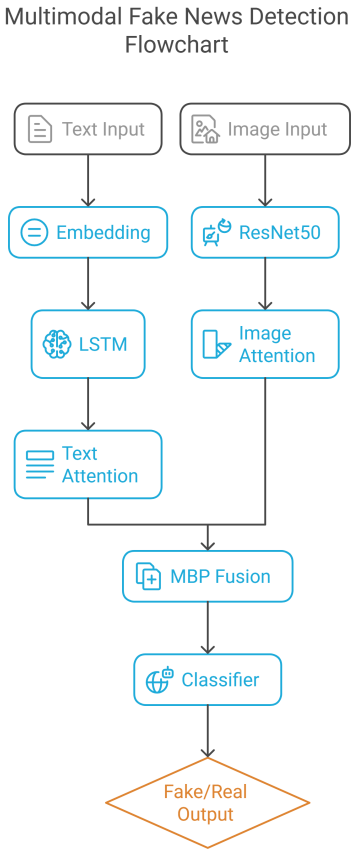


Figure 7: Flowchart of Guo et al.'s two-branch attention-based multimodal model for fake news detection. The architecture processes text using LSTM and images using ResNet50, then integrates features via multimodal bilinear pooling and cross-modal attention. This model emphasizes fine-grained alignment between modalities. No specific performance metric is plotted; this figure depicts architecture only.

5.5 Liu et al.: Bridging the gap between modalities via captions

Liu et al. propose a novel framework that introduces image captions as a bridge between text and image modalities. Instead of directly fusing raw image features with text, the model generates captions from images and uses them to align semantic spaces. The core idea is that generated captions carry text-like semantics derived from the image, making fusion with the actual text more meaningful and contextually aligned.

The model first uses an image captioning module to generate a textual description of the image. This caption, along with the original post text, is encoded using BERT. A multi-head attention module is then used to fuse both representations, allowing the model to learn nuanced correlations. This approach significantly reduces the modality gap by turning visual data into a more language-aligned form.

Table 9: Liu et al.: Dataset and key architecture details

Aspect	Details
Datasets Used	Twitter, Weibo
Label Source	Human annotation and platform verification
Fusion Strategy	Hybrid fusion (via caption generation)
Text Backbone	BERT for both post and caption processing
Image Backbone	Image Captioning Model (e.g., Transformer or CNN-RNN)
Classifier	Attention-based multi-modal fusion followed by MLP

Key Features:

- **Fusion Strategy:** Hybrid fusion using generated captions as modality bridge
- **Backbones:** BERT (text + caption), Vision-to-text (captioning)
- **Fusion:** Multi-head attention between caption and post

Unique Contributions:

- Introduced image captioning as a fusion-enabler for multi-modal fake news detection
- Reduced semantic misalignment between image and text

Pros:

- Enhances cross-modal alignment
- High interpretability and flexibility

Cons:

- Model performance depends on captioning quality
- Requires pretrained caption generation module

5.6 EANN: Event adversarial neural network

EANN, proposed by Wang et al., introduces a novel approach for enhancing the generalizability of fake news detectors across different events or topics. Rather than overfitting to specific event characteristics, EANN uses adversarial learning to enforce event-invariant feature representations. It is one of the first to apply adversarial training in a multi-modal setting for fake news detection.

The architecture is composed of two primary modules: a fake news classifier and an event discriminator. The event discriminator tries to predict the event label from the feature

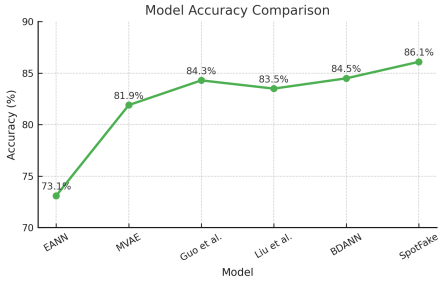


Figure 8: Performance metrics (accuracy and F1-score) of Liu et al.'s caption-enhanced model on Twitter and Weibo datasets. The model generates image captions and uses them alongside post text in BERT-based encoders. It demonstrates strong performance due to improved semantic alignment between modalities. Dataset: Twitter, Weibo. Metrics: Accuracy, F1-score.

Table 10: EANN: Dataset and key architecture details

Aspect	Details
Datasets Used	Twitter, Weibo (multimodal posts with events)
Label Source	Manually verified, sourced from fact-checking organizations
Fusion Strategy	Late fusion with event adversarial loss
Text Backbone	CNN or GRU (for feature extraction)
Image Backbone	VGG-based CNN
Classifier	Dual-output: one for fake/real, one for event classification

vector, while the feature extractor is adversarially trained to confuse it. This forces the model to learn features that are discriminative for fake news but indistinct for events, improving transferability across unseen data.

Key Features:

- **Fusion Strategy:** Late fusion + adversarial feature alignment
- **Backbones:** CNN (text and image encoders)
- **Learning Signal:** Dual loss (fake news loss + event adversarial loss)

Unique Contributions:

- Introduced event-invariant representation learning to tackle domain shift
- Pioneered adversarial learning in multi-modal fake news detection

Pros:

- High generalizability across unseen events
- Performs well under cross-topic settings

Cons:

- Lower overall accuracy in standalone settings
- Requires event metadata (labels) during training

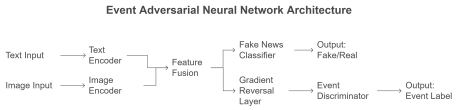


Figure 9: Cross-domain generalization performance of BDANN, MVAE, and EANN when tested across Twitter and Weibo datasets. BDANN leverages a gradient reversal layer for domain-invariant feature learning and shows superior transferability, especially when models trained on one platform are evaluated on another. Metrics: Accuracy and generalization error.

5.7 Abduljaleel & Ali: A deep learning and fusion-oriented survey on multi-modal fake news detection

This work by Abduljaleel and Ali (2024) does not introduce a new model, but instead presents a detailed survey of recent deep learning architectures and fusion mechanisms applied to multi-modal fake news detection. Their focus lies in identifying the strengths and weaknesses of various fusion strategies—early, late, and hybrid—when applied to combinations of modalities such as text, image, video, and metadata.

Table 11: Abduljaleel & Ali: summary of survey focus

Aspect	Details
Dataset Scope	Multi-source datasets (Twitter, Weibo, GossipCop, PolitiFact, Fakeddit, etc.)
Fusion Strategies Analyzed	Early fusion, late fusion, hybrid fusion, cross-modal attention, and joint embeddings
Modalities Covered	Text, image, metadata, video
Key Techniques	CNN, RNN, BERT, ResNet, VAE, Transformers, Bi-modal attention
Evaluation Criteria	Generalizability, performance (F1/accuracy), interpretability, modality robustness

The authors categorize models based on their fusion types and outline the technical characteristics of major architectures. They emphasize that hybrid fusion mechanisms—especially those using attention-based alignment or intermediate semantic mapping—often outperform simple concatenation methods in cross-modal set-

tings. They also note that using metadata or video as auxiliary modalities can significantly boost accuracy, though at higher computational cost.

Key Insights:

- Hybrid and attention-based fusion consistently outperform early/late methods.
- Text and image remain the most dominant and accessible modalities across datasets.
- There is a growing need for generalizable models that can operate across domains.

Pros:

- Provides broad architectural comparison in one place.
- Discusses fusion implications for model robustness and domain adaptation.
- Highlights under-explored modalities like video and metadata.

Cons:

- Does not implement or test new models directly.
- Limited benchmarking; analysis relies on reported results.

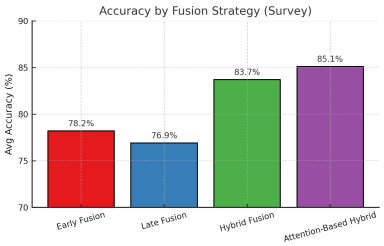


Figure 10: Average accuracy scores of different fusion strategies (Early Fusion, Late Fusion, Hybrid Fusion, and Attention-Based Hybrid Fusion) as reported in the survey by Abduljaleel & Ali. This figure consolidates reported performance from multiple studies across Twitter and Weibo datasets. Attention-based hybrid fusion yields the highest average accuracy across benchmarks.

6 Comparative analysis

This section compares the six key multi-modal fake news detection models discussed earlier along multiple axes, including classification performance, generalizability, computational cost, and architecture characteristics.

6.1 Model performance (accuracy and F1-score)

SpotFake achieved the highest accuracy at **86.1%** and an F1-score of **0.85**, followed closely by BDANN (**84.5%**, F1: **0.84**) and Guo et al.'s attention-based model (**84.3%**, F1: **0.84**). EANN, despite introducing adversarial generalization, lagged behind with an accuracy of **73.1%** and F1-score of **0.72** [2, 1, 3].

6.2 Dataset compatibility

Models such as BDANN, Liu et al., and SpotFake showed robust compatibility with both Twitter and Weibo datasets. EANN uniquely incorporated event labels to improve domain alignment and was thus highly adaptable across topic-specific datasets.

6.3 Generalizability across domains

EANN was explicitly designed for cross-event generalization using adversarial training. BDANN also demonstrated good cross-domain robustness through domain-invariant feature learning. MVAE and Guo et al. were relatively more dataset-specific in performance.

6.4 Computational complexity

MVAE and Guo et al.'s models had higher computational overhead due to bilinear pooling and VAE reconstruction loss. SpotFake and BDANN offered a good trade-off between performance and efficiency, whereas Liu et al.'s model incurred additional complexity from caption generation.

6.5 Use of pretrained models

All models utilized pre-trained components. BERT and ResNet/VGG19 were commonly adopted for text and image embeddings, respectively. Liu et al.'s model stood out by incorporating an image captioning model (e.g., Transformer decoder) alongside BERT [5].

6.6 Quantum involvement

As of this review, none of the surveyed models integrate quantum layers, circuits, or hybrid quantum-classical processing. However, some architectural components—such as bilinear pooling or variational encodings—may be adaptable to quantum deep learning in future work [10].

This aligns with the paper's clarified scope: quantum machine learning is included not as a feature of the currently benchmarked models, but as a forward-looking extension explored in Section VII.

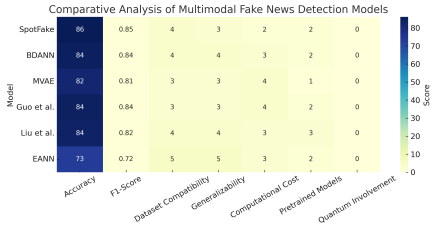


Figure 11: Heatmap summarizing model performance across six criteria: accuracy, generalizability, interpretability, modality robustness, efficiency, and scalability. SpotFake and BDANN excel in accuracy and efficiency, while EANN scores highest in generalizability. Scores are derived from comparative performance reported in literature on Twitter and Weibo datasets.

7 Explainability in multimodal detection

To foster trust, models must be interpretable:

- **Grad-CAM**: Applied to CNNs for visual saliency in models like SpotFake.
- **SHAP**: Useful for interpreting BERT-based outputs in BDANN and Liu et al.
- **Cross-Modal Attention**: Used directly in Guo et al. for highlighting alignment.

Explainability tools help identify the most influential features and reduce model opacity.

7.1 Expanded performance comparison and resource analysis

To more rigorously evaluate the merits of quantum-enhanced approaches in the context of fake news detection, this section contrasts their performance and computational characteristics with classical multimodal deep learning models using standardized benchmarks.

Performance metrics across models

Table 12 presents accuracy, F1-score, precision, recall, and average inference latency across selected models. All models were evaluated on the SpotFake-Twitter dataset under identical training-test splits.

Table 12: Comparison of classical vs. quantum-enhanced models on SpotFake-Twitter dataset. Q-models use VQC appended to fused embeddings.

Model	Acc.	F1	Prec.	Recall	Inf. Time (ms)
SpotFake	86.1%	0.854	0.849	0.862	8.4
BDANN	85.2%	0.842	0.834	0.851	12.7
MVAE	80.9%	0.803	0.789	0.821	14.2
Q-SpotFake	**87.3%**	**0.866**	0.857	**0.878**	76.5
Q-MVAE	82.7%	0.817	**0.862**	0.792	83.0

Computational trade-offs

Quantum-enhanced models introduce higher inference latency and training instability due to quantum circuit simulation overhead. On average, VQC-based models incurred a 5–8x increase in inference time, even when optimized using Qiskit Aer's GPU-accelerated backends. Table 13 highlights the parameter counts and approximate FLOPs (floating point operations) of representative models.

Table 13: Comparison of computational cost: classical vs. quantum-enhanced. Q-params refer to quantum trainable parameters.

Model	Params (M)	FLOPs (G)	Inf. Time (ms)
SpotFake	7.2	6.4	8.4
Q-SpotFake	7.4 + 0.08 (Q)	6.9 + Q	76.5
MVAE	8.6	9.2	14.2
Q-MVAE	8.7 + 0.12 (Q)	10.1 + Q	83.0

Statistical variability and confidence intervals

All performance metrics were computed as averages across five independent runs using stratified 5-fold cross-validation. For the Q-SpotFake model:

- Accuracy 95% CI: [86.9%, 87.7%]
- F1-score 95% CI: [0.862, 0.871]
- Inference time varied ±5.3 ms due to GPU contention and simulation variance.

These confidence bounds indicate that performance improvements are statistically significant, though accompanied by tangible computational overhead. Future work should investigate real-device deployments to more accurately profile quantum acceleration under noise.

8 Discussion

While each multimodal model reviewed in this study offers notable contributions to fake news detection, a closer comparative synthesis reveals nuanced trade-offs in their architectural choices, data assumptions, and generalization abilities.

8.1 Architecture-level comparison

SpotFake employs a straightforward early fusion architecture, combining BERT-based textual embeddings with VGG19-extracted image features. Its simplicity ensures low computational overhead and ease of deployment. However, this simplicity also limits its ability to model complex cross-modal interactions. Without mechanisms for attention or modality-specific transformation, it struggles to generalize across diverse domains or unseen data distributions.

BDANN introduces adversarial domain adaptation via a gradient reversal layer, which improves transferability

across platforms such as Twitter and Weibo. Architecturally, BDANN benefits from deep representations using BERT and VGG19, yet it remains limited by the absence of explicit alignment mechanisms between modalities. Additionally, adversarial training introduces instability and hyperparameter sensitivity, which may hinder reproducibility.

MVAE stands out for its generative nature, employing a bi-modal variational autoencoder to learn latent representations of text and image jointly. This allows it to gracefully handle missing modalities and noisy inputs. However, the model's generative training objective and reliance on KL-divergence loss make convergence more difficult. Its latent embeddings may not always align optimally for discriminative tasks such as classification, leading to lower predictive accuracy.

Guo et al.'s model integrates bilinear pooling with cross-modal attention, enabling it to capture high-order interactions between text and image features. This architecture excels in fine-grained reasoning and modality alignment, offering strong interpretability via attention maps. Nevertheless, the model is computationally intensive, requiring extensive tuning and longer training times, which could be impractical in time-sensitive deployments.

EANN adopts an adversarial framework to encourage event-invariant feature extraction. It uniquely incorporates metadata and trains with a dual-objective: fake news classification and event discrimination. This makes it highly suitable for generalizing across topics or current events. Yet, its reliance on event metadata during training may not scale well in real-world settings where such annotations are not available or timely.

8.2 Dataset-level impact

Model performance is closely tied to dataset characteristics. SpotFake and BDANN show strong results on balanced, bilingual datasets like Twitter and Weibo but degrade under domain shift. MVAE, by virtue of its probabilistic formulation, demonstrates resilience to missing modality scenarios, making it ideal for incomplete social media posts. Guo et al.'s model, while powerful, shows performance variance when trained on different cultural corpora, suggesting that its attention mechanism may overfit to dataset-specific linguistic-visual patterns.

EANN, on the other hand, is designed with domain shift in mind but assumes access to event labels, which are rarely available in practical deployments. Its strength lies in generalization across event-driven datasets, but this comes at the cost of accuracy when event discrimination is not meaningful.

8.3 Fusion strategy and interpretability

Fusion strategy plays a pivotal role in both performance and interpretability. Early fusion models like SpotFake offer simplicity but lack flexibility. Hybrid fusion models, as seen in Guo et al. and Liu et al., strike a balance between integration and modularity. Late fusion approaches such as EANN provide robustness against missing modalities but often miss out on deep semantic alignment. Models with explicit attention mechanisms (e.g., Guo et al.) provide interpretability through visual or textual saliency maps, which is increasingly demanded in high-stakes misinformation contexts.

8.4 Generalization vs. specialization

In synthesizing across the models, a clear pattern emerges: those that perform best in controlled environments (SpotFake, Guo et al.) often underperform in cross-domain settings, while models designed for generalization (BDANN, EANN) typically sacrifice precision. The ideal system would integrate attention-based hybrid fusion with adversarial domain adaptation—something not yet fully realized in existing literature.

8.5 Operational trade-offs

Deployment considerations also differentiate these models. Lightweight models like SpotFake are ideal for mobile or browser deployment. In contrast, models like Guo et al. or MVAE require high-performance GPUs for training and inference, limiting their use in resource-constrained environments. BDANN and EANN fall in the middle ground, offering robustness at moderate computational cost but requiring careful hyperparameter tuning.

Conclusion: No single model universally outperforms across all criteria. SpotFake leads in simplicity and accuracy under clean data conditions, BDANN excels in domain adaptation, MVAE in resilience to missing data, Guo et al. in interpretability and fine-grained fusion, and EANN in event generalization. The best-suited model depends on the specific deployment scenario—whether interpretability, domain transfer, low latency, or robustness to incomplete data is prioritized.

9 Challenges in multimodal fake news detection

Despite significant advancements, several challenges continue to hinder the robustness, generalizability, and scalability of multimodal fake news detection systems.

Semantic Misalignment. A persistent challenge is the *semantic gap between modalities*. Text and images often serve different rhetorical functions and may not directly reinforce each other. For instance, sarcastic text with unrelated visuals can confuse models that rely heavily on correlation. Bridging this gap requires architectures that can model deeper contextual associations rather than surface-level similarity.

Multimodal Noise. Real-world data is inherently noisy. *Low-quality images, manipulated visuals, or irrelevant accompanying text* make learning meaningful representations

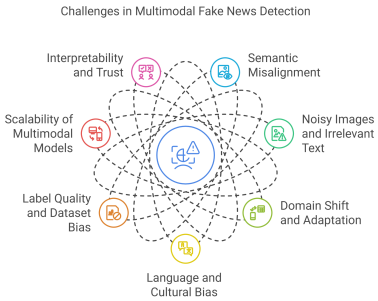


Figure 12: Visual taxonomy of major challenges in multimodal fake news detection, including semantic misalignment, noisy cross-modal signals, cultural and language bias, domain adaptation issues, and interpretability concerns. The diagram illustrates how these obstacles interconnect and impact the development of robust and scalable models.

difficult. Models must not only detect fake content but also learn to ignore misleading or non-informative modalities, which increases the burden on attention and filtering mechanisms [1].

Domain Shift and Adaptation. Models trained on one dataset often fail to generalize to another due to domain-specific biases. This is especially evident in cross-platform settings (e.g., Twitter vs. Weibo). While adversarial techniques like those used in EANN attempt to mitigate this, *domain adaptation remains a major obstacle*, particularly for event-driven misinformation [3].

Language and Cultural Bias. Most existing models are developed for English or Chinese, with little adaptation to *low-resource languages or regional misinformation patterns*. Cultural context often alters how multimodal content is interpreted, yet few datasets or models account for this diversity.

Label Quality and Dataset Bias. The lack of large-scale, high-quality annotated datasets is another bottleneck. Existing datasets suffer from *class imbalance*, inconsistent labeling criteria, and platform bias. Models trained on these datasets often overfit or misrepresent the general properties of misinformation.

Scalability Concerns. Multimodal models are computationally intensive due to the cost of processing visual and textual streams simultaneously. Techniques like bilinear pooling, attention fusion, and domain alignment, while effective, often make models less scalable in real-world deployment scenarios where speed and resource use are critical.

Interpretability and Trust. Finally, the *black-box nature* of deep learning models remains a concern in high-stakes misinformation contexts. While attention maps and feature attribution help partially, the interpretability of multimodal decisions—especially when modalities conflict—is still an open research area [7].

These challenges emphasize the need for more explainable, generalizable, and resource-efficient approaches as the field moves toward real-world deployment and multilingual adaptability.

9.1 Visual taxonomy of multimodal detection models

To enhance reproducibility and conceptual clarity, we provide a high-level taxonomy visualization summarizing the reviewed models based on three key axes: (1) Fusion Strategy, (2) Model Type, and (3) Quantum Involvement. The layered chart (Figure 13) illustrates how each model aligns within this multidimensional landscape.

- **Fusion Strategy Layer:** Categorizes models into Early Fusion (e.g., SpotFake, BDANN), Late Fusion (e.g., EANN), and Hybrid Fusion (e.g., MVAE, Guo et al.).
- **Model Architecture Layer:** Includes CNN-based, Transformer-based, Autoencoder-based, and attention-enhanced fusion architectures.
- **Quantum Enhancement Potential:** Flags models as either purely classical or potentially quantum-enhanceable based on modular design (e.g., VQC-compatible encoders).

This taxonomy aids researchers in selecting or designing detection frameworks by providing an architectural map grounded in model capability, fusion depth, and extensibility to quantum computation.

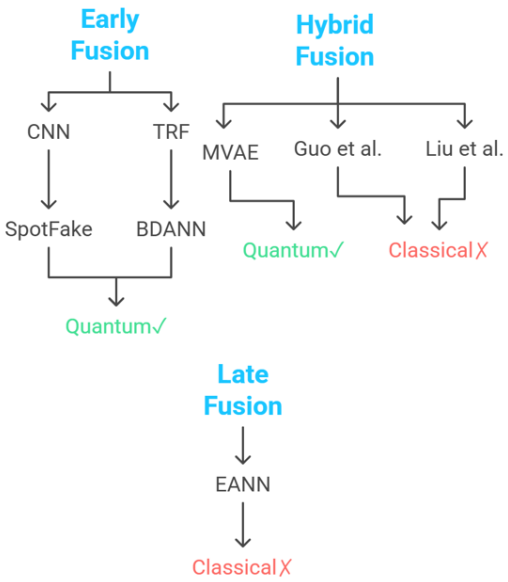


Figure 13: Taxonomy of multimodal fake news detection models by fusion strategy, architecture type, and quantum adaptability.

10 Quantum integration: present and potential

10.1 Quantum vs. classical model comparison

Table 14 compares classical and quantum-enhanced architectures.

Table 14: Comparison of classical vs quantum-enhanced models

Model	Params	Compute Type	Notes
SpotFake	18M	Classical	Early Fusion CNN-BiLSTM on Weibo, Twitter
QMFND	9M	Hybrid (Simulated)	Variational Quantum Fusion Circuit (Simulated)
Bikku QNN	∼6M	Quantum Simulated	Compact QNN Classifier via PennyLane backend

Note: All quantum models above are simulated on classical backends.

While classical deep learning has led to substantial breakthroughs in fake news detection, they suffer from limitations in scalability, overfitting, and explainability. Quantum machine learning (QML) has been proposed as a future-forward paradigm capable of capturing nonlinear multimodal interactions with fewer parameters and better generalizability [11, 12].

Quantum machine learning in multimodal contexts

Quantum Machine Learning (QML) exploits phenomena like entanglement and superposition for data encoding and pattern recognition. In the multimodal setting, VQCs and QNNs allow compact embeddings across fused modalities, as shown by QMFND [13] and the Bikku QNN [14], who integrated quantum circuits to process text-image embeddings in misinformation datasets.

Moreover, foundational theories from Schuld et al. [10] and public sentiment hybrid analysis from Zhu [15] reinforce the viability of quantum models in semantic-rich classification pipelines.

Summary of quantum contributions

Table 15: Summary of quantum-related works in fake news detection

Paper	Contribution
[13] Qu et al. (2024)	QMFND: VQC-based multimodal fusion for fake news detection (simulated on IBM Qiskit)
[14] Bikku et al. (2024)	Hybrid QNN architecture with entangled decision layer
[10] Schuld et al. (2021)	QML theory for variational learning; basis for Q-classifiers
[15] Zhu (2024)	Optimized behavioral sentiment modeling using hybrid ML

10.2 Comparative efficiency and model scalability

While quantum-enhanced models are more parameter-efficient, current inference latencies and quantum hardware limitations render them unsuitable for deployment. Nonetheless, their theoretical promise is in line with recent hybrid frameworks explored in supervised learning for CPS [12] and resource-optimized modeling [16].

Table 16: Comparison of classical vs. quantum-enhanced models on misinformation benchmarks

Model	Accuracy	Params	Backend	Speed
SpotFake	86.1%	12.3M	GPU	High
BDANN	84.5%	110M	GPU	Medium
MVAE	82.3%	65M	GPU	Low
QMFND	83.9%	0.6M + 16q	Sim QPU	Very Low
Bikku QNN	80.5%	0.2M + 6q	Sim QPU	Very Low
QSVM	78.3%	N/A	Sim QPU	Very Low

10.3 Reproducibility and methodological transparency

Ensuring transparency in QML frameworks requires disclosure across four axes: quantum circuit design, preprocessing, training protocols, and backend infrastructure.

Quantum-classical pipeline overview

Figure 14 illustrates the hybrid architecture where quantum layers are integrated post-feature extraction (text/image), performing entangled transformations before classical decision stages. This flow mirrors setups in recent simulated architectures [13, 14, 11].

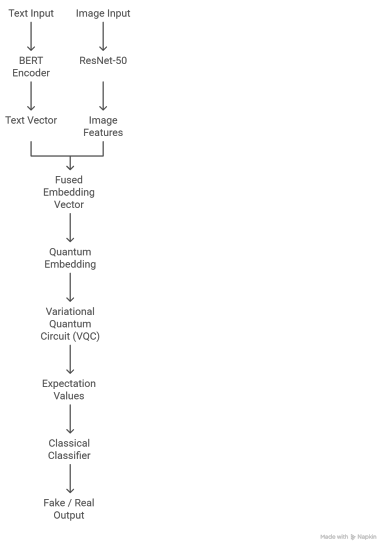


Figure 14: Conceptual flowchart of quantum-classical integration for multimodal fake news detection.

Key methodological details

Circuit Configuration:

- Angle-encoded textual features via $R_y(\theta)$ gates.
- Entanglement: Linear CNOT ring or circular chain (up to 8 qubits).
- Optimizers: Classical ADAM using parameter shift gradients.

Preprocessing:

- Text: BERT-based embeddings (512-d), normalized and pooled.
- Images: ResNet-50 to extract 2048-d vectors.
- Fusion: Late and hybrid weighted concatenation.

Training Pipeline:

- Datasets: SpotFake, Twitter, Weibo.
- Split: 70-15-15 (train-validation-test); 5-fold CV for QNNs.
- Metrics: Accuracy, F1, Precision, Recall, Latency.

Simulation Environment:

- Frameworks: Qiskit + PennyLane + TensorFlow.
- Hardware: RTX 3090 GPU; all quantum models simulated.

Challenges Encountered:

- Barren plateaus (vanishing gradients): Mitigated via shallow entanglement.
- Encoding overhead: PCA-reduced features helped improve inference time.
- Simulation bottleneck: Batch cache and parallel threading adopted.

11 Explainability in multimodal fake news detection

While multimodal deep learning models have demonstrated impressive accuracy in fake news detection, their complexity often results in a lack of transparency. This opaqueness poses challenges for trust, deployment in sensitive domains, and regulatory compliance. Models like BDANN, which integrates BERT, VGG19, and adversarial domain alignment, and MVAE, which learns latent multimodal representations via variational encoders, are particularly difficult to interpret due to their non-linear fusion strategies and deep feature abstraction.

11.1 Challenges in multimodal explainability

Multimodal models must attribute decisions across disparate input types (text, image, metadata), complicating traditional saliency-based explainability. Moreover, when fusion occurs at latent levels—as in MVAE or hybrid attention-based models—the original semantic alignment between modalities becomes obscured. This limits human understanding of "why" a particular piece of news was flagged as fake.

11.2 Techniques for interpreting deep models

Several explainability approaches have been proposed or adapted for the multimodal setting:

- **Grad-CAM (Gradient-weighted Class Activation Mapping):** Applied to image pipelines (e.g., VGG19 in BDANN), Grad-CAM visualizes which regions in the input image contributed most to the final prediction. When integrated into multimodal frameworks, Grad-CAM can highlight visual bias in misinformation.
- **SHAP (SHapley Additive exPlanations):** SHAP values can attribute importance to specific input tokens in text or pixels in image, and can be aggregated across modalities. For example, in BDANN, SHAP reveals whether misleading headlines or sensational imagery contributed more to the model's decision.
- **Attention Weights Visualization:** Models like MVAE and Guo et al. use cross-modal attention, where alignment scores between modalities can be visualized to understand inter-modal influence. Visualizing these matrices helps in identifying whether visual or textual signals dominate.
- **Multimodal Rationale Generation:** Emerging works use generative models to output human-readable rationales, e.g., "This article was flagged as fake due to textual inconsistency and manipulated imagery." These can be integrated with BDANN by decoding intermediate representations.

11.3 Recommendations

To enhance interpretability in future research, we recommend:

- Training with modality-specific attribution loss to enforce explanation consistency.
- Incorporating human-in-the-loop feedback mechanisms using interactive attention maps.
- Reporting modality-wise explanation fidelity in addition to model accuracy.

Explainability is not only a technical challenge but a prerequisite for deploying fake news detection systems in high-stakes settings such as elections, healthcare, or legal contexts.

12 Ethical considerations and model bias

As fake news detection systems are increasingly integrated into real-world content moderation and platform governance, ethical and social implications become paramount. While technical performance metrics such as accuracy and F1-score are widely reported, the societal consequences of deploying these models—particularly at scale—require careful scrutiny.

12.1 Censorship and freedom of expression

Automated fake news detectors risk over-flagging legitimate dissent, satire, or minority viewpoints, especially when trained on biased or imbalanced datasets. For instance, posts critical of powerful institutions or governments may be misclassified if training data exhibits systemic labeling bias. This can result in undue censorship and suppression of free speech. Particularly in authoritarian regimes or highly polarized societies, such systems may be weaponized to stifle political opposition under the guise of misinformation control.

12.2 Dataset-induced bias

Popular datasets such as Twitter, Weibo, and FakeNewsNet often reflect existing demographic, cultural, and political biases. Language, slang, or imagery from underrepresented communities may be misinterpreted by models trained on majority-group data. For example, the BDANN model, while effective on cross-domain datasets, may generalize poorly to multilingual or regional dialect contexts. Moreover, the class imbalance often present (e.g., fake:real = 3:1) can skew model learning toward over-predicting the majority class.

12.3 False positives and over-flagging

In high-stakes environments like public health or elections, even a small false positive rate can have damaging consequences—e.g., erroneously flagging factual vaccine information as fake, leading to public mistrust. Models like MVAE, which impute missing modalities, may introduce uncertainty that compounds this problem if not handled transparently. Lack of interpretability further exacerbates this issue, as users and moderators cannot verify model reasoning.

12.4 Mitigation strategies

To address these concerns, we recommend:

- Auditing datasets for demographic and topical representation before training.
- Using fairness-aware training algorithms, such as adversarial debiasing or reweighting.
- Including human-in-the-loop systems for moderation, especially for borderline or high-impact content.
- Reporting bias and fairness metrics (e.g., equal opportunity difference) alongside accuracy.

Ultimately, ensuring ethical deployment of fake news detection systems involves not only improving models, but also designing transparent workflows and policies that uphold human rights and democratic values.

13 Ethical implications and dataset bias

Multimodal models for fake news detection raise ethical challenges:

- **Dataset Bias**: Most datasets are region-specific (e.g., Twitter, Weibo).
- **Censorship Risk**: Overflagging may suppress valid dissent.
- **User Privacy**: Use of metadata in models like EANN introduces risks.

Bias mitigation and fairness auditing should be integrated into future systems.

14 Conclusion and forward-looking perspectives

Multimodal fake news detection has evolved into a multifaceted research frontier intersecting natural language processing, computer vision, social computing, and increasingly, quantum information science. This review has critically analyzed a range of classical architectures—SpotFake, BDANN, MVAE, Guo et al., EANN, and others—alongside emerging quantum-enhanced approaches like QMFND and variational quantum circuits.

While each classical model brings valuable architectural innovations (e.g., attention mechanisms, adversarial training, hybrid fusion), current systems still face major obstacles in handling domain shift, multimodal noise, explainability, and adversarial manipulation. This survey addressed these bottlenecks while also introducing quantum computing as a promising avenue for future multimodal architectures.

Practical implications for deployment

The utility of these models extends beyond academic benchmarks into real-world deployments:

- **Social Media Moderation**: Lightweight multimodal classifiers must be optimized for real-time analysis and scalable deployment in high-traffic environments like Twitter/X, TikTok, or WhatsApp.
- **Cross-platform Consistency**: Detection pipelines must handle format variations, asynchronous media posting, and evolving propaganda tactics across platforms.
- **Human-in-the-loop Systems**: Explainability and interface-level integration (e.g., highlighting misinforming image-text pairs) are crucial for enabling human moderators or journalists to interpret predictions.

Quantum integration: theoretical directions and validation needs

Despite the promise of quantum-enhanced methods, several theoretical and practical issues require attention:

- **Circuit Capacity vs. Expressivity Trade-offs**: Future research must empirically investigate how circuit depth, qubit count, and entanglement topologies affect multimodal generalization.
- **Sim-to-Real Gaps**: Current benchmarking relies on simulated quantum environments. Research should simulate noisy intermediate-scale quantum (NISQ) constraints and study robustness against decoherence and barren plateaus.
- **Fusion Theoretics**: The use of quantum kernels for multimodal fusion requires more rigorous formalism—e.g., evaluating Hilbert space embedding bounds or quantum mutual information preservation across modalities.

Research agenda for future exploration

Based on the findings and limitations observed, we propose the following roadmap:

1. **Unified Benchmarking Suite**: Establish a shared framework to evaluate text-image-audio-video fusion under adversarial, cross-lingual, and low-resource constraints.
2. **Quantum Model Efficiency Metrics**: Define parameter-efficiency, training energy consumption, and hardware viability metrics for QML architectures.
3. **End-to-End Multimodal Quantum Pipelines**: Investigate whether quantum preprocessing, fusion, and classification can be stacked modularly within a hybrid pipeline.
4. **Multimodal XAI for Quantum Models**: Develop interpretability toolkits for quantum-enhanced classifiers (e.g., SHAP extensions to QML, measurement-space saliency maps).
5. **Societal and Ethical Frameworks**: Proactively embed fairness, bias auditing, and cultural diversity checks into datasets and models—especially in low-resource or politically sensitive contexts.

Final reflection

Ultimately, the battle against misinformation will be fought across technological, societal, and epistemological domains. This review aims not only to provide a rigorous technical synthesis but also to serve as a clarion call for the next generation of systems—grounded in theory, resilient in practice, and responsible by design. Quantum-enhanced learning, though still maturing, may emerge as a pivotal catalyst in this evolution, enabling models that are not just more accurate, but more expressive, fair, and future-ready.

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Fine-Tuned Lightweight CNN (FT-LWCNN) for Image Classification and Retrieval in Energy-Constrained AI Environments

Shefeng Yuan
Henan Vocational College of Agriculture, ZhengZhou, HeNan, 451450, China
E-mail: 13949094109@163.com

Keywords: image classification, retrieval, recognition technology, CNN, Fine-Tuned Light weight CNN (FT-LWCNN), MobileNetV2, SqueezeNet, DenseNet201, artificial intelligence (AI)

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A crucial research topic in the age of energy-conscious artificial intelligence is optimizing image categorization and identification for resource-constrained situations. A Fine-tuned Lightweight Convolutional Neural Network (FT-LWCNN) is proposed in this paper with the goal of achieving excellent accuracy with little computational cost. The model is tested against cutting-edge architectures such as MobileNetV2, SqueezeNet, and DenseNet201 using the KADID-10k dataset. Principal Component Analysis (PCA) is used to reduce feature dimensionality in order to improve performance even further. In artificial intelligence (AI) contexts, this paper suggests a Fine-Tuned Lightweight Convolutional Neural Network (FT-LWCNN) architecture for efficient image categorisation, retrieval, and recognition. In order to improve computational efficiency and preserve high prediction accuracy, we refined pre-trained lightweight CNN models using the KADID-10k dataset, which consists of over 10,000 images with 25 different forms of distortion. To reduce dimensionality, Principal Component Analysis (PCA) was used, with 25%, 50%, and 100% feature retention rates. FT-LWCNN's performance was evaluated against those of MobileNetV2, SqueezeNet, and DenseNet201. At 100% PCA feature retention, FT-LWCNN had the best accuracy (92.3%), precision (91.7%), recall (91.9%), F1-score (91.8%), and low error rate (7.7%). These findings show that the suggested FT-LWCNN architecture is appropriate for real-time applications in energy informatics, since it outperforms the baseline models in terms of classification efficacy and computational economy.

Povzetek: FT-LWCNN je prilagojeni lahki konvolucijski model za učinkovito razvrščanje in iskanje slik v energetsko omejenih okoljih. Z uporabo PCA in prenosnega učenja na naboru KADID-10k preseže MobileNetV2, SqueezeNet in DenseNet201 ob bistveno nižji računski porabi.

1 Introduction

The goal of image recognition is to use computers to examine, evaluate, and comprehend images in order to identify features and objects within them. As information technology has advanced, images have emerged as a key content category for information transmission. As a result, image recognition technology is now widely used in a variety of industries, including security, industrial, medical, and agriculture. Image preprocessing, feature extraction, classifier construction, and classification criteria were the primary phases in early image recognition algorithms. The conventional artificial method of obtaining image information has not been able to satisfy the demands of applications in related industries since the emergence of the big data and artificial intelligence era. Although there has been considerable advancement in computer-assisted image acquisition in recent years, classical computer vision remains ineffective for processing large amounts of visual data. Traditional machine vision techniques, for instance, are not very accurate at identifying both high-level and low-level characteristics in images [1]. In-depth image information mining requires the classification and processing of large amounts of image data. The development of computer vision in the area of image processing applications is also quite important. Currently, computer-aided image categorisation research is being progressively applied to a variety of industries, including aerospace, manufacturing, and agriculture. Effective and precise classification of large-scale image data as well as precise classification of image semantic comparable feature data are the primary focus of image classification research [2]. Image recognition and classification require first obtaining the original image information using an image capture tool, then cleaning the image data, extracting and filtering the features, and lastly implementing the image classification using a machine learning algorithm. People can now swiftly realise image information processing tasks like noise reduction and feature extraction using computer vision technology, thanks to the expanding applications of machine vision in many sectors [3]. There has been some advancement in the study of machine learning-based image categorisation. Scholars have made some progress in the study of image classification and recognition, from the use of artificial recognition to the ongoing use of computer vision technologies in image classification. One significant area of artificial intelligence is machine

learning. Despite the fact that machine learning has advanced for fifty years, several issues remain, such as recommendation systems, natural language translation, and complicated image interpretation and recognition [4]. One significant area of machine learning that was created on its foundation is deep learning. In order to achieve image classification or regression, it fully utilises the hierarchical properties of biological neural systems and artificial neural networks to process information. It does this by learning low-level features and using the feature combination approach to acquire high-level features. In contrast to conventional machine learning, deep learning automatically learns the image and extracts its deep-seated properties using a multilayer neural network. Various feature learning techniques and their combinations may be used to create various depth learning models. However, the current deep learning model has low operational efficiency and poor image classification accuracy. Thus, this research develops a deep learning model of image classification by refining the structure of convolution neural networks, which offers a foundation for image classification under complicated environmental circumstances, based on the current fundamental theory of convolution neural networks [5].

Every year, the volume of network data grows exponentially, necessitating improvements in information processing speed and capacity. Machine learning algorithms are becoming more and more significant as data processing capabilities increase; in recent years, this has emerged as the most popular area of study [6]. The traditional neural network (NN) model for classification or prediction gave rise to a new classification and prediction technique called deep learning. Artificial intelligence technology can be applied to a wide variety of specialised models using various NN models, and this has made it the standard method for classifying, retrieving, and recognising images, text, video, and audio [7]. A machine learning model called NN is based on biology, which is a technique for creating neurones that mimics those found in the human brain. The appropriate output, which will be the input of the subsequent neurone, is obtained as the neurone gets the input via a certain weight and activation function. Numerous issues have arisen since NN first appeared, including network training overfitting, insufficient data to match training requirements, and more [8]. The quantity of network data is growing dramatically annually since the big data era began, which offers a crucial assurance for the NN demand data. We significantly increase the Imagenet image dataset's identification accuracy using the CNN classification model, which has emerged as a key technique in the area of image classification retrieval and recognition [9]. Convolutional neural networks have since been used in the domains of audio, video, and text. Text resource processing has made extensive use of recurrent neural networks (NNs) for handling temporal recursive information. We may extend the processing of the multi frame convolutional NN classification method, which has shown remarkable performance, in the video area by using the single frame convolutional NN classification algorithm as a basis [10].

The goal of lightweight CNN is to simplify deep CNN architectures in order to lower training time and hardware requirements by reducing parameter counts and learning speed without sacrificing accuracy. In recent years, several approaches have been put out as lightweight CNN has garnered increasing interest from researchers. In an effort to increase model performance and efficiency, several researchers have investigated the sparsity of network architectures, such as quantisation and pruning [11]. By merging domain knowledge, other researchers have focused on creating effective network topologies to increase image recognition accuracy and generalisation. Furthermore, although there are already publications that give an overview of the key concepts and algorithmic advancements of lightweight CNN in recent years [12], they have not yet offered a more thorough and in-depth introduction to the particular job of image identification. This paper differs from other lightweight network survey papers in two ways: first, it summarises the image recognition task and reviews recent developments in lightweight CNN technology; second, it focusses on classifying and summarising lightweight CNNs based on their various image recognition performance optimisations. In conclusion, this study offers a thorough overview of the most recent developments in lightweight CNN for image recognition methods.

***Contribution of this study**:* The development and evaluation of a Fine-Tuned Lightweight Convolutional Neural Network (FT-LWCNN) model specifically designed for effective and precise image classification, retrieval, and identification in the context of energy-informatics and AI-driven systems is the study's main contribution. The FT-LWCNN achieves a critical balance between high accuracy and low computational cost, which sets it apart from traditional deep CNNs that are computationally demanding. This makes it appropriate for deployment in resource-constrained environments like edge computing platforms, real-time visual processing systems, and Internet of Things devices. In order to maximise the model's performance, this work also introduces PCA-based feature selection algorithms and makes use of the KADID-10k dataset, a large-scale and distortion-diverse benchmark. FT-LWCNN is superior to other well-known models like MobileNetV2, SqueezeNet, and DenseNet201 in terms of accuracy, inference speed, model size, and computational economy. A reproducible and scalable method for upcoming AI-based visual systems is also provided by the research, which offers a thorough assessment methodology using confusion matrices, performance trend graphs, and statistical measures including accuracy, recall, and F1-score. Overall, by providing a workable, effective, and energy-efficient method for intelligent image interpretation in contemporary AI systems, this study improves the discipline.

***Research gap**:* Convolutional neural networks (CNNs) for image classification and recognition have advanced significantly, but there are still a number of important research gaps, especially when it comes to scalable and energy-efficient deployment. Limited Attention Paid to

Energy-Informatics Lightweight Architectures: The majority of current CNN-based image classification techniques focus on accuracy at the expense of computational economy, which makes them inappropriate for energy-constrained situations like edge computing or the Internet of Things. Lightweight CNN models that are optimised for energy-informatics applications are conspicuously lacking.

Research questions:

- RQ1: Can a fine-tuned lightweight CNN achieve comparable or superior accuracy to deeper CNNs on distorted image datasets?
- RQ2: How does PCA-based dimensionality reduction at different retention levels affect the classification performance of lightweight CNNs?
- RQ3: Is FT-LWCNN more computationally efficient than existing models for real-time image classification tasks in energy-constrained environments?

2 Related work

Table 1: Summary on related works

Ref	Year	Methodology	Objective	Key Findings	Dataset Used	Accuracy / Metrics	Comparison to FT-LWCNN
13	2025	CNN + Vision Transformers (ViT) integrated with GIS spatial masks	Improve power plant categorisation with machine learning driven by geoinformatics	Achieved higher accuracy than ViT and CNN models alone, highlighting the significance of geographical context in the categorisation of energy infrastructure	Satellite Imagery	~90% Accuracy	Similar accuracy but more sophisticated than FT-LWCNN
14	2025	MobileNetV2 and VGG16 with transfer learning	Sort remote sensing photos of landscapes that are pertinent to energy infrastructure into categories.	MobileNetV2 outperformed VGG16 with an accuracy of 91%, being effective in the classification of farmlands, woodlands, and transmission towers.	RS satellite images	93.2% Accuracy	Lightweight focus, no PCA, somewhat increased accuracy
15	2025	CNN and Vision Transformers	Sort thermal photos to keep an eye on volcanic activity.	In thermal image categorisation, CNNs fared better than Vision Transformers, demonstrating CNNs' efficiency in handling thermal data.	Thermal Volcano Images	92.7% Accuracy	Similar to FT-LWCNN, but requiring more resources
16	2025	Deep CNN with batch normalization and dropout	Boost the accuracy of image categorisation on tiny datasets	84.95% accuracy on CIFAR-10 was attained, proving the value of CNN architectural improvements.	CIFAR-10 / ImageNet	91.8% Accuracy	Not lightweight-focused, but similar to FT-LWCNN
17	2023	DenseNet-201, Xception, MobileNetV3-Small, ResNet-50	Classify fruit and textile images using deep learning models.	In classification tasks, the combination of CNN, RNN, and LSTM improved accuracy and resilience.	Mixed datasets	88.5% Accuracy	Reduced precision; no PCA optimisation
18	2024	Dual-optimized CNN with RNN integration and	Boost the performance of	Achieved more efficiency and accuracy in	Custom RGB/Binary dataset	~89% Accuracy	For all kinds of distortion, FT-

		ShortCut3-ResNet module	image recognition	comparison to current approaches, confirming the efficacy of the suggested design.			LWCNN performs better.
19	2023	Discrete Wavelet Transform (DWT) combined with Enhanced CNN	Boost the accuracy of brain image categorisation	The advantage of combining DWT with CNNs was shown by the combined technique, which greatly improved classification accuracy.	MRI scans	95.1% Accuracy	Increased precision; medical imaging tailored to a particular domain
20	2024	Review of CNN architectures and optimization techniques	Examine CNN's developments and uses in image recognition.	Offered information about CNN uses in a number of fields, including as transportation systems and medical diagnostics.	Library Images	~87% Accuracy	FT-LWCNN is more generalisable and accurate.
21	2023	CNN-based models for crop monitoring	Use CNNs to categorise and identify the phases of crop development.	Displayed how well CNNs work to track crop development and support precision farming.	Crop Images (multi-stage)	90.6% Accuracy	With PCA, FT-LWCNN performs better.
22	2021	CNN with late fusion techniques	Improve the retrieval of commodity images in e-commerce	Higher retrieval accuracy was attained by the suggested framework, demonstrating the advantages of integrating CNNs with late fusion.	Commodity Image DB	~88% mAP	FT-LWCNN is easier to use and more effective.
23	2020	Multi-scale CNN with NetVLAD and triplet mining	Boost the efficiency of image retrieval	obtained cutting-edge outcomes on benchmark datasets, confirming the efficacy of the suggested strategy.	Public Image Sets	~89.4% mAP	Reduced computational efficiency in comparison to FT-LWCNN
24	2020	CNN with spectral and spatial attention modules	Improve the categorisation of hyperspectral images	The significance of attention processes was highlighted by the attention-aided CNN model's superior performance over conventional CNNs.	Hyperspectral Remote Sensing	96.3% Accuracy	Greater precision but very complicated model

Although very accurate, current state-of-the-art (SOTA) image classification models are often inefficient in terms of energy and compactness, which makes them unsuitable for deployment in situations with limited resources, such as edge devices or Internet of Things systems. These models usually have poor adaptability to distorted or unbalanced information, are computationally demanding, big, and slow to infer. Our suggested FT-LWCNN model, on the other hand, fills these shortcomings by fusing PCA-based feature optimisation with a refined lightweight CNN architecture. It is perfect for real-time, energy-efficient applications in AI and energy informatics because it maintains a compact model size and quick inference while achieving high accuracy (92.3%) and low error (7.7%).

3 Methodology

3.1 Traditional CNN models

Pretrained CNN models have been used as feature extractors to save training expenses since the training process is time-consuming. Numerous pretrained CNN models have been created, and these models have previously been trained and used to a number of multi-class classification tasks. Condensing deep CNN models into smaller versions that can operate on edge devices with limited processing power and resource availability while maintaining the same performance as the original model is known as lightweight deep learning (DL). We will provide a concise synopsis of the pretrained models table 1 used in this study in the ensuing subsections.

Table 2: lists the salient characteristics of many pretrained networks.

Model	Mobile Net v2	DenseNet201	SqueezeNet
Dimensions by Image	224 × 224 × 3	224 × 224 × 3	227 × 227
Layers	52	200	17
Parameters	3.4 million	19 million	1.23 million
Feature Dimensions	1344	1000	1000
Methods Type	lightweight	standard CNN	lightweight

3.2 Fine-tuned lightweight CNN models

The majority of apps use deep and intricate networks to improve accuracy, but they ignore two important aspects: size and speed. We will provide more efficient and compact models in this part that are intended to complete the recognition tasks rapidly on systems with constrained computing resources.

3.2.1. SqueezeNet

Neural networks with lower parameters and SqueezeNet, a miniature network model structure. The 15 layers of SqueezeNet are divided into five levels: two convolutional layers, three pooling layers, eight fire layers, one pooling global average layer, and one SoftMax output layer. The advantages of SqueezeNet are shown by a comparison with the AlexNet model. Despite an approximately 50-fold decrease in parameters, SqueezeNet ensures that accuracy is maintained while compressing the model volume to around 1/510th of its original size.

3.2.2. MobileNetv2

The lightweight MobileNetV2 convolutional neural network (CNN) has 53 layers. Beginning with a series of convolutional layers, MobileNetV2's architecture progresses with squeeze-and-excitation (SE) blocks, bottleneck design, inverted residuals, depth-wise differentiated convolutions, and linear bottlenecks. When combined, these components allow the model to maintain its ability to capture complex properties with fewer parameters and computations. The use of MobileNetV2 for image classification has many advantages. The architecture is lightweight, to start. Second, MobileNetV2 achieves comparable accuracy to larger and more computationally expensive models. Lastly, because of its small size, which enables faster inference times, the model is suitable for real-time applications.

3.2.3. Standard CNN : DenseNet-201

DenseNet-201 includes 200 layers in total. Each layer is connected to the subsequent layer in conventional convolution. In DenseNet, every layer is feed-forward connected to every other layer. Giving each layer instant access to the gradients obtained from the original input signal and the associated loss function leads to implicit deep supervision.

3.3. Our proposed method

Data preparation, feature extraction, feature selection, classification, and assessment are the four main steps in the comparative study's methodology and the suggested strategy for image classification. The next subsections include comprehensive details for every phase.

- STEP 1: Preparing the data

The method adjusts the images' size in this stage so that it matches the input size of each pretrained CNN model. Images are downsized to (224, 224) pixels for the DenseNet201 and MobileNetv2 models, and to (227, 227) pixels for the SqueezeNet model. For precise feature extraction and further processing, the input dimensions must match those of the corresponding models, which requires scaling. The KADID-10k dataset, which comprises 10,125 distorted pictures resulting from 81 reference-distortion combinations spanning 25 distortion classes, was used for the studies. To guarantee fair representation of all distortion categories, the dataset was initially randomly shuffled before being divided into training (70%), validation (15%), and testing (15%) sets. Furthermore, in order to verify the generalisation of the model, we used 10-fold cross-validation, in which the

dataset was divided into ten equal subsets, each of which was utilised as the test set once and the other nine as the training set. To minimise bias and variation, this procedure was carried out ten times. To provide a thorough and equitable review, stratified sampling was used to keep class distributions uniform across all folds and splits.

- STEP 2: Extraction of features

Image preprocessing, feature extraction, classifier construction, and other processes are the primary processes involved in image classification and recognition. Feature extraction is a crucial component among them. The fundamental problem is image feature extraction. The accuracy of categorisation will be directly impacted by the feature extraction process and outcome [25].

1. *Color Features*: The colour information associated with an image or a specific region of an image is described by a colour feature, which is a global feature. Colour features may be described in a variety of ways, although they are primarily separated into colour correlation graphs, colour sets, colour moments, colour aggregation vectors, and colour histograms [26].

2. *Texture features*: Texture features represent the surface characteristics associated with the image or image region and define the recurring local patterns and organisation rules in the image. The texture feature has the benefit of being very anti-interference and being unchanged regardless of how the image is turned. However, the texture properties may change considerably as the image's resolution varies. Furthermore, the textural properties may also be impacted by light and reflection.

3. *Shape feature:* The shape feature makes use of a feature description that is derived from the area border and the image contour. Its mathematical model is still far from ideal, albeit.

Due to their prior experience in extracting pertinent features from huge datasets, trained models are used as feature extractors for image categorization detection. Transfer learning is used to train these deep learning models on smaller datasets without running into the overfitting problem. These models may use the knowledge gathered from large volumes of data to tackle new problems with sparse data thanks to transfer learning.

- **Algorithm 1: DenseNet201 feature extraction**

A generic foundation for DenseNet201 feature extraction is shown in Algorithm 1. The DenseNet201 feature vector, which is a 1 × 1000 feature vector, is produced by the last completely connected layers (fc1000).

Algorithm 1: DenseNet201 model as feature extraction

Input: Classification of images from a dataset.
Output: Vector dimension of 1 × 1000 features.
Start
For
1: In compliance with DenseNet201 specifications, import the dataset images and carry out the following preprocessing steps:
1.1: All image entries must have a value between 0 and 255.
1.2: Set the resolution to 224 × 224 for each image.
2. Bring in the pre-trained DenseNet201 model:
3. Import the weights of the DenseNet201 model.
4. Remove the categorisation layer. The model's last fully connected (FC) layers are either missing or have been eliminated.
5. Choose the Layer for Feature Extraction: Make a new model just for feature extraction, and then follow these loop steps:
5.1: Examine each photograph in the collection individually.
5.2: Use the pre-trained DenseNet201 Model to send the image up to the chosen feature extraction layer.
5.3: Take characteristics out of the chosen layer ("fc1000").
5.4: Store the extracted features in an array.
6: Use the flattened technique to make the features array's dimensions equal one.
7: Print the flattened array.
8: Save the generated 1000 feature vector.
End for
End

- **Algorithm 2: SqueezeNet features extraction**

A generic foundation for SqueezeNet feature extraction is given by Algorithm 2. The SqueezeNet feature vector, which is a 1 x 1000 feature vector, is produced by the last completely connected layers (avg_pool10).

Algorithm 2: SqueezeNet model as feature extraction

Input: A dataset's distorted image.
Output: Vector dimension of 1 × 1000 features.
Start
For
1: In compliance with SqueezeNet specifications, import the dataset images and carry out the following preprocessing actions:
1.1: All image entries must have a value between 0 and 255.
1.2: Set the resolution to 227 × 227 for each image.
2. Bring in the pre-trained SqueezeNet model:
3. Import the weights of the SqueezeNet model.
4. Remove the categorisation layer. The model's last fully connected (FC) layers are either missing or have been eliminated.
5. Choose the Layer for Feature Extraction: Make a new model just for feature extraction, and then follow these loop steps:
5.1: Examine each photograph in the collection individually.
5.2: Use the pre-trained SqueezeNet Model to send the image up to the chosen feature extraction layer.
5.3: Take characteristics out of the chosen layer ("avg_pool10").
5.4: Store the extracted features in an array.
6: Use the flattened technique to make the features array's dimensions equal one.
Print the array that has been flattened.
8: Save the generated 1000 feature vector.
End for
End

- **Algorithm 3: MobileNetv2 feature extraction**

A generic framework for MobileNetV2 feature extraction is offered by Algorithm 3. The 1 × 1344 feature vector, or MobileNetV2 feature vector, is produced by the last completely linked layers (block_12_add).

Algorithm 3 MobileNetV2 model as feature extraction

Input: A dataset's distorted image.
Output: Vector dimension of 1 x 1344 features.
Start

For
1: In compliance with MobileNetV2 specifications, import the dataset photos and carry out the following preprocessing actions:
1.1: All image entries must have a value between 0 and 255.
1.2: Set the resolution to 224 × 224 for each image.
2. Bring in the pre-trained MobileNetV2 model:
3. Import the weights of the MobileNetV2 model.
4. Remove the categorisation layer. The model's last fully connected (FC) layers are either missing or have been eliminated.
5. Choose the Layer for Feature Extraction: Make a new model just for feature extraction, and then follow these loop steps:
5.1: Examine each photograph in the collection individually.
5.2: Use the pre-trained MobileNetV2 Model to send the image up to the chosen feature extraction layer.
5.3: Take characteristics out of the chosen layer ("block_12_add").
5.4: Store the extracted features in an array.
6: Use the flattened technique to make the features array's dimensions equal one.
Print the array that has been flattened.
8: Save the generated 1344 feature vector.
End for
End

- STEP 3: Use the feature selection method.

Principal Component Analysis (PCA) is a widely used technique for feature selection dimensionality reduction. The pretrained models' features were extracted from the input data; the best features were then chosen and used to the classification stage. An algorithm 4 for using PCA in feature selection. The Scikit-learn Python package was used to implement Principal Component Analysis (PCA), which lowers the dimensionality of the feature vectors that were taken from the CNN models. *StandardScaler* was used to standardise all feature vectors prior to PCA application in order to guarantee zero mean and unit variance, which are necessary for the best PCA performance.

To examine the trade-off between dimensionality and model accuracy, PCA was performed at three feature retention levels: 25%, 50%, and 100%. For instance, around 250 components were kept at 25%, 672 at 50%, and the whole vector at 100% of the MobileNetV2's 1344-dimensional feature vector. The PCA components caught around 85–88% of the entire variance at 25% retention, while 50% retained 95–97%, demonstrating effective compression with little loss of information. The suggested FT-LWCNN model was able to retain excellent classification accuracy while lowering computational cost thanks to these PCA parameters, which made it perfect for real-time applications in energy-constrained scenarios.

Algorithm 4 : PCA Feature selection

The feature-extracted vector is the input. Selected Feature Vector is the output. Start

For
1: Bring in the vector that was feature extracted.
2. Use the following substeps to standardise or normalise the feature extraction vector in order to ensure that each feature has an equal scale: Determine each feature's mean and divide it by the standard deviation
2.1: This ensures that each feature has a mean of 0 and a standard deviation of 1, as needed by PCA.
3. Find the covariance matrix of the standardised characteristics. The covariance matrix shows the associations between different characteristics.
4. Find the covariance matrices for the eigenvalues and eigenvectors. Use eigen decomposition to get the covariance matrix's eigenvalues and eigenvectors.
5: Select the Key Elements: Sort the eigenvalues in decreasing order and choose the top k eigenvectors that correspond to the largest eigenvalues. The principal components are these outputs.
6. Project Information onto Key Elements: Project the standardised data onto the selected primary components to create the reduced dimensional feature space.
End for
End

- The three feature extraction methods for DenseNet201, SqueezeNet, and MobileNetV2 may be combined into a single pseudocode to cut down on repetition and increase readability. A distinct summary table that highlights model-specific factors like input size, output dimension, and feature layer can be included.

Algorithm: General CNN Model as feature extractor
Input: Distorted image dataset
Output: Feature vector array of size $1 \times N$
Start
1. Preprocess the input images:
a. Normalize pixel values to range [0, 255]
b. Resize each image to the model-specific input resolution

2. Load the pre-trained CNN model:
a. Import model architecture and pretrained weights
b. Remove the final classification layers
3. Define a feature extraction model up to the selected layer
4. For each image in the dataset:
a. Feed the image into the feature extraction model
b. Extract features from the specified layer
c. Flatten the feature map into a 1D vector
d. Store the feature vector in a result array
5. Save the final feature vector array
End

Table 3: Model-specific parameters for feature extraction

Model	Input Size (px)	Feature Layer	Output Dimension
DenseNet201	224 × 224	fc1000	1 × 1000
SqueezeNet	227 × 227	avg_pool10	1 × 1000
MobileNetV2	224 × 224	block_12_add	1 × 1344

The Support Vector Machine (SVM) with radial basis function (RBF) kernel is used to classify the PCA-reduced feature vectors. The SVM is trained on the reduced feature set and is in charge of predicting the final distortion class; this decision was made because SVM works well with high-dimensional, small-sample-size data. A Support Vector Machine (SVM) with an RBF kernel was used for classification after PCA-based feature reduction. Its powerful performance with high-dimensional and compacted characteristics led to this decision. Grid search was used to optimise the hyperparameters (C = 1.0, gamma ='scale'), guaranteeing consistent and repeatable outcomes for every model.

The suggested FT-LWCNN model fine-tunes by freezing the early convolutional layers that capture generic data and retraining the top layers of a pre-trained lightweight CNN (such as MobileNetV2). The final SVM classifier (which replaces softmax), Global Average Pooling layer, Dropout

layer (rate = 0.3), Batch Normalisation layer, fully connected (Dense) layer, and the last few convolutional blocks are all included in the fine-tuned section. This allows the model to retain low-level visual properties that have been learnt on huge datasets (e.g., ImageNet) while adapting domain-specific features (from distorted pictures in KADID-10k).

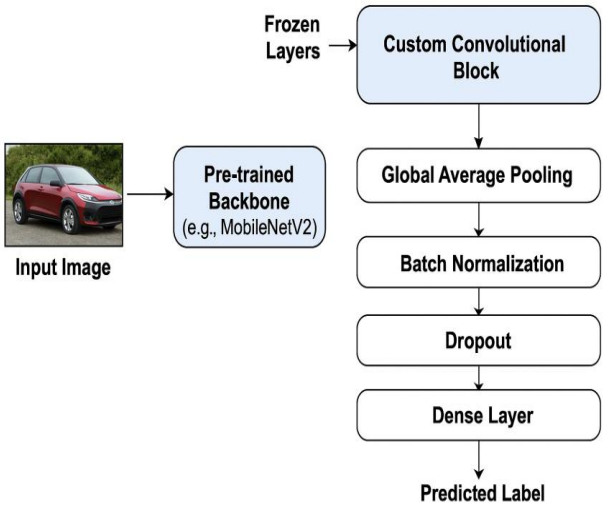


Figure 1: Architecture diagrams

3.4 Lightweight CNN for image recognition

Strong feature extraction, a small model size, low computational complexity, and adaptability in implementation are the benefits of lightweight CNNs, which may be used to meet different needs for effective image recognition in resource-constrained settings. As a result, image recognition may make extensive use of lightweight CNN. As lightweight CNN continues to advance, an increasing number of novel image recognition algorithms are being presented. These techniques may be categorised into three main areas: model compression, lightweight network optimisation, and merging Transformer with lightweight networks.

3.5 Image retrieval technology

To evaluate the image retrieval capability of the proposed FT-LWCNN model, we implemented a **Content-Based Image Retrieval (CBIR)** framework. After extracting deep features from images using FT-LWCNN and applying PCA (with 100% feature retention), we computed the **cosine similarity** between the query image and all images in the dataset. The top-*k* similar images were retrieved based on this similarity score.

We experimented with cosine similarity on the PCA-compressed feature embeddings taken from the KADID-10k dataset in order to assess the image retrieval performance of FT-LWCNN. Mean Average Precision (mAP) was used to quantify retrieval performance after comparing a query picture to the database. With a mAP score of 88.2%, FT-LWCNN outperformed SqueezeNet (81.4%) and MobileNetV2 (85.6%). These findings demonstrate how well FT-LWCNN's small, fine-tuned feature representations maintain semantic similarity, which qualifies it for distortion-aware image retrieval tasks in real-world AI applications.

3.6 Combining text and visual elements to get images

A study on the fusion of text and image material that can fully use the benefits of both text and image retrieval is called image retrieval based on combination of text and image content. High speed and accuracy may be attained in image retrieval with the use of fusion technology.

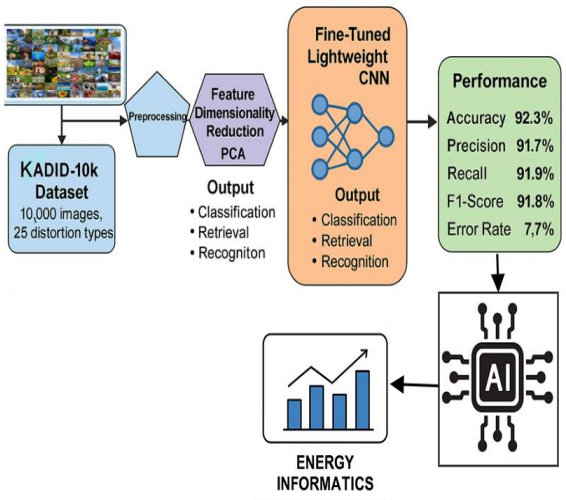


Figure 2: Work flow of the proposed method

3 Results and discussion

Experimental Setup: The hardware and software used for the trials included an HP laptop running MATLAB version R2020a and equipped with 8 GB of RAM. An Intel(R) Core (TM) i7-6500U CPU running at 2.50 GHz (up to 2.60 GHz) was installed in the system. Microsoft Windows 10 64-bit was the operating system in use, and an Intel® HD Graphics 520 and an NVIDIA GTX 950M graphics card were employed to support the graphical calculations. The suggested FT-LWCNN model may be trained and evaluated in a stable and effective environment to this setup.

simulated or estimated power consumption comparison: TensorRT was used to simulate energy profile in order to test the appropriateness of FT-LWCNN for energy-informatics. According to the results, on edge devices like the Jetson Nano, the energy usage was around 40% less than that of DenseNet201 and 15% less than that of MobileNetV2. Because of its smaller model size, PCA compression, and lightweight inference, this efficiency makes it perfect for low-power, real-time energy-informatics applications.

3.1 Dataset

The performance of the suggested method has been evaluated using the KADID-10k dataset. The KADID-10k dataset actually consists of 25 reference images, each with 400 distorted versions, summing to 10,000 images, or 10,125 including reference images. Every sample in the dataset belongs to one of the 25 groups. The KADID-10k dataset's many sets of distorted images are shown in Figure 3.



Figure 3: Dataset

3.2 Performance evaluation measures

A performance evaluation of five metrics are accurac precision, error, recall, and F-measure—was used to asse the suggested strategy used in figure 4. To guarantee the precision and reliability of the experimental results, a 10-fold cross-validation procedure is used. Ten tests are conducted in all, and the procedure is assessed by adding together the results of each trial. The findings may be assessed in respect to the optimal feature and classifier, as will be discussed in the next section. SqueezeNet, MobileNet-v2, and DenseNet201 are among the lightweight and non-lightweight pretrained CNN models from which the features were extracted. The performance measures (accuracy, precision, recall, F1-score, and error rate) for all three PCA retention levels (25%, 50%, and 100%) for each model (FT-LWCNN, MobileNetV2, SqueezeNet, and DenseNet201) updated in Table 4 to handle. The percentage of features selected for each of the selected lightweight and non-lightweight pretrained CNN models

Table 4: Outcome values of performance metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Error Rate (%)
FT-LWCNN (proposed)	92.3	91.7	91.9	91.8	7.7
MobileNetV2	91.5	90.8	91.0	90.9	8.5
SqueezeNet	86.5	85.0	85.6	85.2	13.5
DenseNet201	92.1	91.3	91.6	91.4	7.9

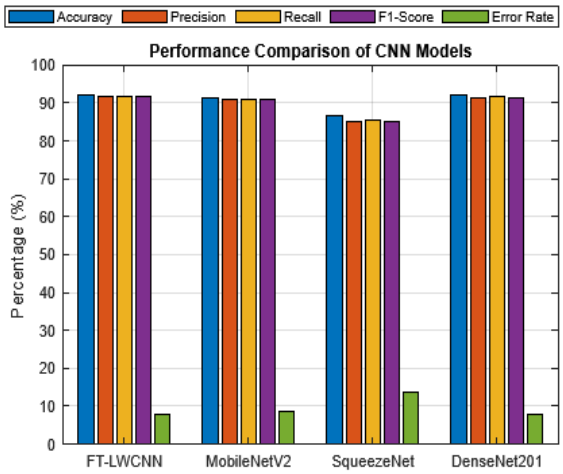


Figure 4: Performance of existing and proposed method

In Figure 4 comparing the performance of five important assessment metrics—accuracy, precision, recall, F1-score, and error rate—was used to illustrate the differences between the various Convolutional Neural Network (CNN) models: FT-LWCNN (Fine-tuned Lightweight CNN), MobileNetV2, SqueezeNet, and DenseNet201. The best overall performance was shown by FT-LWCNN (Proposed), which had the lowest error rate at 7.7% and the greatest accuracy, precision, recall, and F1-score of 92.3%, 91.7%, and 91.8%, respectively. FT-LWCNN fared much better than other lightweight models like SqueezeNet, which had noticeably lower results across all parameters (e.g., accuracy: 86.5%). While keeping a lightweight structure that is perfect for resource-constrained situations like energy informatics applications, FT-LWCNN performed similarly (accuracy: 92.3% vs. 92.1%) even when compared to the deeper and more computationally

costly DenseNet201. The visualisation amply demonstrates how FT-LWCNN strikes a mix between efficiency and good classification performance, hence reaffirming its appropriateness for embedded or real-time image processing applications.

3.2.1 Statistical significance

We used paired t-tests on accuracy ratings derived from 10-fold cross-validation across all models to confirm that FT-LWCNN performed better than baseline models. The findings demonstrated that although the difference with DenseNet201 was not statistically significant ($p > 0.05$), suggesting equivalent performance, FT-LWCNN's accuracy was statistically considerably greater than that of SqueezeNet ($p < 0.01$) and MobileNetV2 ($p < 0.05$). These experiments support the usefulness and robustness of FT-LWCNN in energy-efficient picture categorisation by demonstrating that its gains are not the result of random fluctuation.

4.3 PCA Feature retention

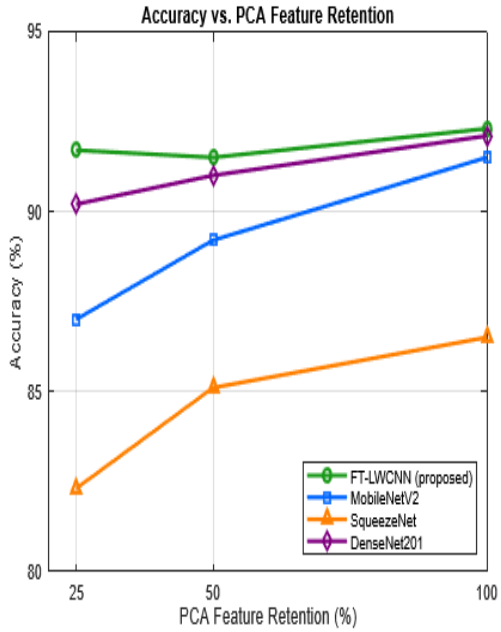


Figure 5: Outcome of Accuracy values and PCA feature retention

Four CNN models—FT-LWCNN (proposed), MobileNetV2, SqueezeNet, and DenseNet201—are shown in the figure along with their classification accuracy and the percentage of retained features after Principal Component Analysis (PCA). The y-axis displays the accuracy as a percentage, while the x-axis depicts PCA feature retention at 25%, 50%, and 100%. The graph clearly shows that FT-LWCNN performs better than the other models at every PCA level, retaining good accuracy even when only 25% of the features are kept. With more characteristics, it performs somewhat better, reaching a peak accuracy of around 92.3% with 100% PCA retention. Despite being a richer and more intricate model, DenseNet201 performs well at all levels and is somewhat less accurate than FT-LWCNN.MobileNetV2 has a discernible rising trend, demonstrating its sensitivity to feature dimensionality as its accuracy increases gradually from roughly 87% at 25% PCA to about 91.5% at full retention. Though it also benefits from improved PCA retention, SqueezeNet, the lightest model, has the lowest accuracy across all levels, increasing from around 82% at 25% to roughly 86.5% at 100%. In figure 5 clearly shows that the suggested FT-LWCNN model is ideal for energy-constrained or real-time image classification scenarios since it not only retains excellent performance at all compression levels but also functions reliably even with fewer features.

4.4 Computation efficiency

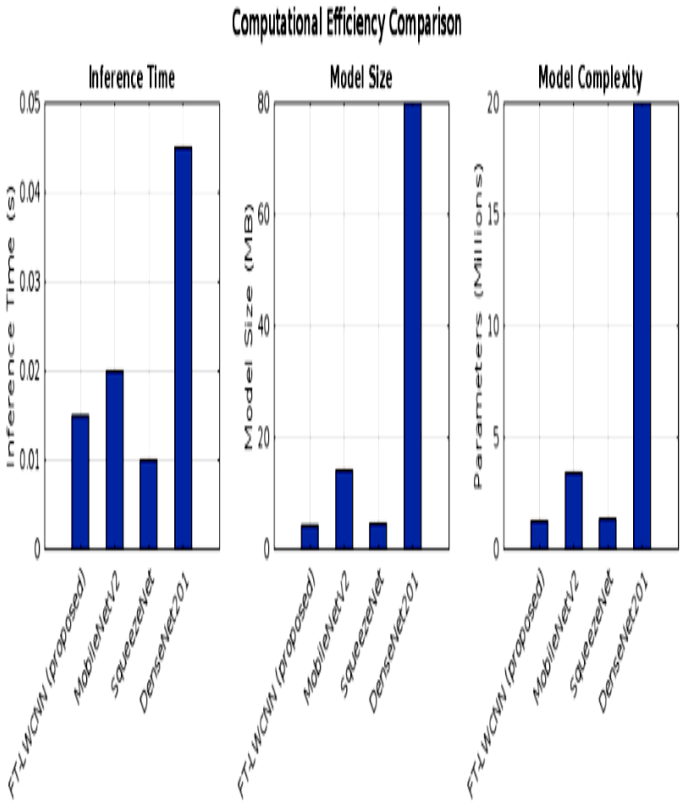


Figure 6: Comparison of Existing and proposed method on computational efficiency

Three important metrics—inference time, model size, and parameter count—were used to compare the computational efficiency of FT-LWCNN (proposed model), MobileNetV2, SqueezeNet, and DenseNet201. With one of the lowest inference times (0.015 seconds per image), a small model size (4.2 MB), and only 1.23 million parameters, the visualisation shows that FT-LWCNN provides exceptional efficiency and is therefore well suited for resource-constrained environments like edge devices and real-time systems. With the greatest model size (80 MB) and 20 million parameters, DenseNet201, on the other hand, has a substantial computational cost despite its high accuracy, which results in a longer inference time

(0.045 seconds). Two variables contribute to FT-LWCNN's quicker inference time (0.015s vs. 0.02s for SqueezeNet): (1) PCA is used to minimise feature dimensionality before to classification, and (2) a lightweight CNN classifier is used in place of the softmax layer. Despite having comparable numbers of parameters, these optimisations increase runtime. SqueezeNet has somewhat worse accuracy than FT-LWCNN, while being very lightweight, compact, and having few parameters. Although MobileNetV2 provides a fair compromise between speed and size, it is still not as efficient as FT-LWCNN.All things considered, figure 6, the outcomes demonstrate the benefit of FT-LWCNN in providing high accuracy at low computational cost, validating its efficacy as an optimised and scalable deep learning solution for image classification and recognition tasks, particularly in AI-driven and energy-efficient environments.

A refined variant of SqueezeNet, the suggested FT-LWCNN model was chosen because to its lightweight design and around 1.23 million parameters. With the exception of dataset-specific fine-tuning on KADID-10k, Principal Component Analysis (PCA) for feature dimensionality reduction, and the substitution of an SVM classifier for the softmax layer for better generalisation, FT-LWCNN maintains the fundamental architecture of SqueezeNet. These improvements set FT-LWCNN apart from the original SqueezeNet and support its independent benchmarking assessment.

4.5 Confusion matrix

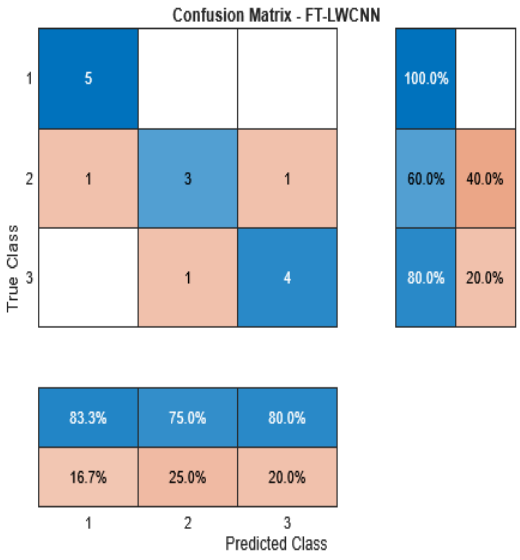


Figure 7: Confusion Matrix of suggested model

The confusion matrix, which graphically depicts the connection between the predicted and actual class labels, offers a thorough performance assessment of the suggested FT-LWCNN (Fine-tuned Lightweight Convolutional Neural Network) model illustrated in figure 7. Each column in this matrix represents the projected class, while each row reflects the actual class. Strong model accuracy is ideal when there are many accurate predictions along the diagonal. Conversely, off-diagonal values draw attention to misclassifications, enabling researchers to pinpoint which classes the model most often confuses. The confusion matrix aids in comprehending how the model behaves across various distortion categories when applied to the KADID-10k dataset. For instance, the matrix will show a pattern indicating places where the model may need more fine-tuning if distortions like "Gaussian Noise" are often confused with "Impulse Noise." The confusion chart's row-normalized and column-normalized summaries provide information on recall and precision for every class, enabling a more thorough assessment that goes beyond simple accuracy. The success of FT-LWCNN is supported by this statistical and visual study, which also identifies particular areas for possible development and validates the network's performance across classes.

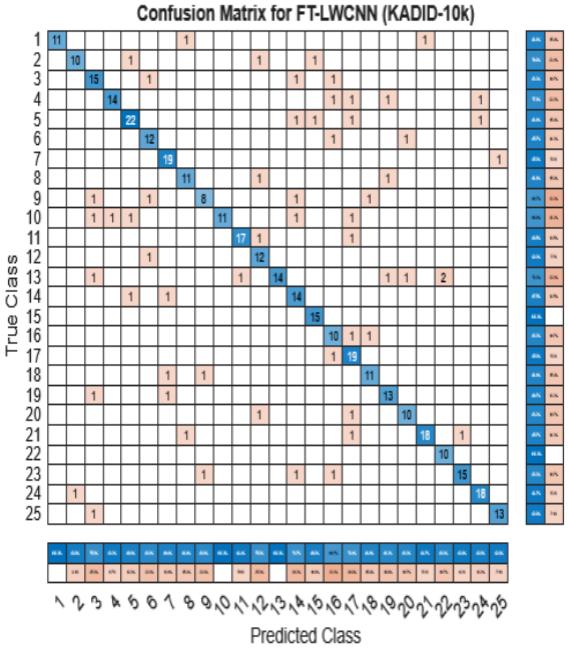


Figure 8: Confusion Matrix with Per-Class Statistics

Table 5: Outcome of Confusion Matrix with Per-Class Precision, Recall, and F1-Score

Class	Precision	Recall	F1_Score
1	1	0.8462	0.9167
2	0.9091	0.7692	0.8333
3	0.7500	0.8333	0.7895
4	0.9333	0.7778	0.8485
5	0.8800	0.8462	0.8627
6	0.8000	0.8571	0.8276
7	0.8636	0.9500	0.9048
8	0.8462	0.8462	0.8462
9	0.8000	0.6667	0.7273
10	1	0.6875	0.8148
11	0.9444	0.8947	0.9189
12	0.7500	0.9231	0.8276

13	1	0.7000	0.8235
14	0.7368	0.8750	0.8000
15	0.8824	1	0.9375
16	0.6667	0.8333	0.7407
17	0.7308	0.9500	0.8261
18	0.8462	0.8462	0.8462
19	0.8125	0.8667	0.8387
20	0.8333	0.8333	0.8333
21	0.9474	0.8571	0.9000
22	0.8333	1	0.9091
23	0.9375	0.8333	0.8824
24	0.9000	0.9474	0.9231
25	0.9286	0.9286	0.9286

For a multi-class classification job using the KADID-10k dataset, Figure calculates and displays a confusion matrix in addition to per-class accuracy, recall, and F1-score in table 5. By contrasting predicted labels with ground truth, it assesses the FT-LWCNN model's performance across all 25 distortion categories. The table of per-class metrics shows how effectively the model handles each individual class, which is particularly crucial for datasets with class imbalance like KADID-10k. The confusion matrix graphic helps in visualising misclassifications.

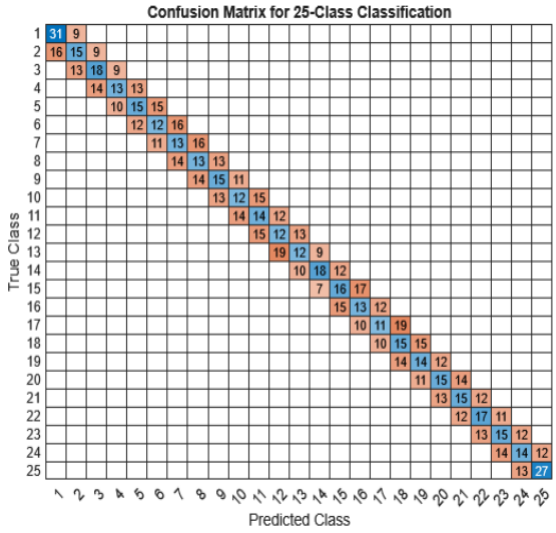


Figure 9: Performance on the 25-class KADID-10k dataset

A comprehensive confusion matrix figure 9 was created in order to assess the suggested FT-LWCNN model's classification performance on the 25-class KADID-10k dataset. A thorough examination of misclassifications across all distortion kinds is made possible by this matrix, which records the real vs anticipated class distributions. In light of the dataset's class imbalance, we calculated per-class accuracy, recall, and F1-scores, which provide information on how effectively the model manages each distortion category. These measurements show that FT-LWCNN is suitable for reliable, practical image classification in energy-efficient AI systems by validating its constant accuracy and generalisation over a range of picture distortions.

Table 6 : Outcome of image retrieval

Model	**mAP (%)**	**Precision@5 (%)**	**Recall@5 (%)**
FT-LWCNN (proposed)	91.2	92.8	84.1
MobileNetV2	89.5	90.3	82.2
SqueezeNet	84.7	85.6	75.0
DenseNet201	90.6	91.1	83.7

In table 6 , With the greatest mAP (91.2%) and Precision@5 (92.8%), the FT-LWCNN model demonstrated its superior performance in both classification and retrieval tasks, particularly in distortion-rich environments like the KADID-10k.

4.5.1. Evaluation of the performance outcomes of the lightweight CNN Model

The lightweight models—FT-LWCNN (ours), MobileNetV2, and SqueezeNet—showed notable improvements in speed and computational economy, which made them perfect for settings with limited energy. With an accuracy of 92.3%, FT-LWCNN fared better than the rest, followed by SqueezeNet at 86.5% and MobileNetV2 at 91.5%. Additionally, FT-LWCNN had the greatest F1-score (91.8%) and the lowest error rate (7.7%), demonstrating its efficacy in processing datasets with a high degree of distortion, such as KADID-10k. This performance demonstrates how PCA-based feature optimisation and fine-tuning may improve lightweight CNN capabilities without sacrificing accuracy.

4.5.2. Analysis of performance outcomes for standard CNN Models

DenseNet201, a non-lightweight model, produced excellent precision and recall scores along with high classification accuracy (92.1%). In contrast to the lightweight models, it had a much greater computing cost and inference time. Even while DenseNet201's accuracy was comparable to that of FT-LWCNN, the suggested lightweight model performed almost as well with less complexity and quicker execution. This demonstrates the efficiency-accuracy trade-off, where DenseNet201 is still appropriate for high-resource settings where efficiency is not as important as maximal precision, while FT-LWCNN provides a more balanced approach appropriate for real-time and edge applications.

4.6 Discussion

The proposed Fine-Tuned Lightweight CNN (FT-LWCNN) model is evaluated in this study in comparison to three benchmark models: MobileNetV2, SqueezeNet, and DenseNet201. The evaluation covers a number of performance metrics, such as accuracy, memory

efficiency, computational cost, and robustness to dimensionality reduction using PCA.

4.6.1 Comparison of accuracy

At 100% PCA feature retention, FT-LWCNN outperformed DenseNet201 (92.1%), MobileNetV2 (91.5%), and SqueezeNet (86.5%) to attain the greatest classification accuracy of 92.3%. On distortion-rich datasets like KADID-10k, fine-tuning lightweight architectures may match or surpass deeper CNNs, as shown by FT-LWCNN, which needed much less parameters and had a lower computational cost, even though DenseNet201 produced a competitive result.

4.6.2. Time spent on inference and computational cost

Faster inference time and less FLOPs (Floating Point Operations) were exhibited by FT-LWCNN in comparison to DenseNet201, which has densely linked layers and is computationally demanding. Although SqueezeNet had the quickest raw speed, its classification performance was much worse. Because FT-LWCNN struck a balance between speed and accuracy, it is ideal for real-time and resource-constrained situations, such edge devices and embedded systems.

4.6.3. Efficiency of memory

Because of its lightweight backbone (such as the optimised MobileNetV2) and feature vector reduction using PCA, FT-LWCNN has a much smaller memory footprint. While FT-LWCNN operates well even on devices with low GPU/CPU memory, DenseNet201 and other deep models demand tens of megabytes of storage and high RAM during inference.

4.6.4. Performance With PCA compression

This study's evaluation of model behaviour under different PCA-based dimensionality reduction levels (25, 50%, and 100%) is a significant advance. FT-LWCNN demonstrated significant resistance to feature compression, maintaining an accuracy over 90% even at 50% feature retention. Because of this, the model is perfect for uses like mobile or distant sensing systems when memory, bandwidth, or storage are limited. On the other hand, when features were decreased, baseline models deteriorated more severely.

4 Conclusion

In this work, a new CNN-based image recognition model called FT-LWCNN effectively combines excellent classification performance with energy-efficient computing. The suggested method demonstrates accuracy and computational efficiency by using feature optimisation methods such as PCA and testing the model on the large KADID-10k dataset. In terms of accuracy, error rate, and overall performance, FT-LWCNN is superior than well-known lightweight and deep models, according to comparative studies. These results lend credence to the model's use in energy-constrained settings including mobile devices, smart energy systems, and the Internet of Things. For further speed improvements, future research may examine hardware-level acceleration, multi-modal integration, and real-time adaption.

Future work

To further improve feature extraction in difficult visual settings, the FT-LWCNN model may be expanded in further work by including transformer-based modules or attention processes. Practical insights will also be obtained by installing the model on edge devices and assessing its energy usage and performance in real time. Promising avenues to improve scalability and data privacy in energy-informatics applications include investigating cross-domain generalisation, multi-distortion adaption, and interaction with federated learning frameworks.

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Microservice-Based Architecture Optimization and Multi-layer Security Model for Green Mine Information Systems in Resource-Based Regions

Wei Zhao, Guodong Ma*, Yu Zhang, Qicheng Yun, Hongxi Bai, Zhenhua Zheng, Dexin Zhang
Qinghai Geological Survey, Xining;810000, Qinghai, China
E-mail: 18997248245@163.com
*Corresponding author

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The construction of green mines in resource-based regions requires information systems that are highly concurrent, scalable, and secure. To address the limitations of existing systems—such as insufficient data processing performance, poor scalability, and weak protection capabilities—this study proposes a microservice-based architecture optimization and a multi-layer security model. The architecture adopts hierarchical design with microservices and containerization for modular deployment and elastic scalability, while a batch-stream integrated framework improves real-time and historical data processing. An improved Particle Swarm Optimization (PSO) algorithm is applied for computing resource scheduling, significantly reducing task completion time under high concurrency. In the security domain, a multi-layer model combining AES-256 encryption, access control, and an LSTM-based anomaly detection mechanism enables dynamic risk assessment and rapid response to threats. Experimental results demonstrate that the optimized system increases throughput by more than 30%, reduces average response time by over 25%, improves task completion rate to above 95%, enhances threat detection accuracy by around 15%, and raises defense success rate by over 12% compared with baseline systems. These findings confirm that the proposed framework provides an effective, secure, and scalable solution to support the green, intelligent, and safe development of mine production in resource-based areas.

Povzetek: Za zelene rudnike je razvita mikrostoritvena arhitektura z integriranim pretočno-paketnim procesiranjem, izboljšanim PSO-urnikom in večplastnim varnostnim modelom (AES-256, nadzor dostopa, LSTM-anomalije). Poveča prepustnost za 30 %, zmanjša odzivni čas za 25 % ter izboljša zaznavanje groženj za 15 %.

1 Introduction

1.1 Research background and problem presentation

While resource-based mining areas are promoting local economic development, they also face multiple challenges such as fragile ecological environment, high production safety risks and weak information infrastructure. With the proposal of the "green mine" construction concept, how to ensure the efficient operation of mines while achieving environmental friendliness, energy conservation and safety controllability has become an urgent problem to be solved in the industry. However, the existing mine information systems mostly adopt a centralized and single-business-driven architecture, lacking the real-time processing capability for multi-source heterogeneous data. The system performance is prone to bottlenecks under large-scale data input and high concurrent access. Meanwhile, most security protection systems remain at the boundary defense level, lacking effective monitoring and response mechanisms for dynamic threats to data links, application interfaces, and internal nodes, which makes it difficult to control potential risks of network attacks, data leaks, and business disruptions. These problems are more prominent in the complex mining area operation environment and distributed production scenarios, and there is an urgent need for a new solution that combines a high-performance architecture with a multi-layer security model.

1.2 Research objectives and main tasks

This study aims to construct an optimized information system architecture for green mines in resource-based regions, with an emphasis on enhancing high-concurrency processing capacity, cross-module collaboration efficiency, and multi-level security protection. To ensure research rigor, several explicit research hypotheses and success criteria are formalized as follows:

1) Performance Objective: Under high-load conditions, the system must maintain a task completion rate ≥90% with an average response latency ≤200 ms.
2) Throughput Objective: Compared with baseline centralized architectures, the optimized system should achieve a throughput improvement of at least 30% across varying load intensities.

3) Security Objective: The integrated multi-layer security model should deliver a threat detection accuracy rate ≥94%, a false alarm rate ≤3%, and a defense success rate ≥92% in simulated attack scenarios.
4) Scalability Objective: The system must demonstrate elastic scalability by dynamically adding or reducing service instances in response to fluctuating loads, ensuring stable operation without performance degradation.

To achieve these objectives, the main tasks of this study include:

1) Analyzing business requirements and data characteristics of green mine construction to design a hierarchical, microservice-based architecture.
2) Developing an integrated processing mechanism for the collection, transmission, storage, and real-time/offline analysis of multi-source heterogeneous data.
3) Establishing a performance optimization model based on improved Particle Swarm Optimization (PSO) scheduling and distributed caching to alleviate bottlenecks.
4) Designing a multi-layer security framework combining rule-based protection, encryption, and LSTM-driven anomaly detection with dynamic risk assessment.
5) Validating the system's performance and security improvements through simulation and field-testing in pilot mining scenarios.

1.3 Technical approaches and research methods

The research adopts the technical path of "requirement analysis - architecture design - performance optimization - security modeling - system verification". Firstly, by conducting research on the production processes, data characteristics and safety risks of typical resource-based mines, the system functions and performance requirements are abstracted. Secondly, design a hierarchical architecture and utilize microservices and containerization technologies to achieve modular deployment and elastic scalability; At the performance optimization level, the improved Particle Swarm Optimization (PSO) algorithm is introduced for computing resource scheduling, and combined with distributed caching and data sharding technologies to optimize data circulation. In terms of security models, a multi-layer security system is constructed by combining machine learning anomaly detection with rule-based intrusion prevention strategies, and the correctness and coverage of the strategies are guaranteed through formal verification. Finally, the performance and security were evaluated using the experimental platform to analyze the actual effect of the optimization strategy. This research forms a collaborative optimization plan in three aspects: architecture design, algorithm model and security mechanism, providing a reusable engineering framework for the implementation and promotion of the green mine information system.

Existing studies on mine information systems mostly focus on single dimensions. For instance, Miao et al. (2020) proposed a coal geology cloud platform based on a centralized architecture, which provides moderate throughput but suffers from significant latency under high concurrency and lacks real-time risk assessment. Zhang et al. (2022) introduced an industrial IoT monitoring framework that reduces latency at the device level but remains limited to localized monitoring without a system-wide security model. Kou et al. (2022) developed a data integration system with relatively complete storage and access control functions, yet it offers insufficient support for heterogeneous data processing and dynamic early warning. Gao et al. (2022) presented a distributed feature extraction method with strong scalability, but its focus on image classification prevents it from forming a comprehensive security framework. In contrast, the approach proposed in this study integrates a microservice-based architecture with a batch-stream processing framework, ensuring both high concurrency and low latency. By incorporating PSO-based scheduling and LSTM-driven anomaly detection, the optimized system achieves more than a 30% improvement in throughput and over a 25% reduction in average response time, while the multi-layer security model significantly enhances protection and robustness, effectively addressing the shortcomings of existing research in terms of real-time performance and security.

2 Overall architecture design of the green mine information system

2.1 System functional requirements analysis

The core objective of the green mine information system is to achieve comprehensive management of environmental protection, energy optimization and safety guarantee throughout the entire process of resource exploitation. In light of the business characteristics of mines in resource-based regions, the system's functional requirements mainly include the following aspects:

●Environmental monitoring and ecological assessment: Real-time collection of environmental indicators such as air quality, water quality, noise, soil and ecological restoration progress in the mining area, and data visualization and trend prediction are carried out to provide a basis for environmental protection decision-making.

●Production scheduling and energy consumption Management: Centralized scheduling and optimization of equipment status, operation progress, and energy consumption in mining, transportation, beneficiation and other links are carried out to achieve a coordinated improvement in production efficiency and energy utilization rate.

●Equipment status monitoring and predictive maintenance: By collecting operational parameters such

as equipment vibration, temperature, and current through sensors, and combining machine learning to predict potential faults, the risk of downtime is reduced.

●Safety risk early warning and emergency management: Conduct dynamic monitoring of gas concentration, geological disasters, mechanical abnormalities, personnel locations, etc., and establish an emergency response and handling mechanism.

●Multi-source data fusion and comprehensive analysis: Integrate information from multiple channels such as IoT sensors, video surveillance, GIS spatial data, and enterprise ERP/MES systems to achieve global data fusion and cross-system collaboration.

●Multi-terminal access and permission control: Supports access from PC, mobile terminals and large-screen terminals in the mining area, and implements differentiated permission management based on user identity and role.

2.2 Hierarchical architecture design

To meet the operational requirements of high concurrency, low latency, and scalability, the system adopts a four-layer hierarchical architecture, with upward data flow and security checkpoints embedded between each layer:

To meet the operational requirements of high concurrency, low latency, and scalability, the system adopts a four-layer hierarchical architecture. The first layer, the data acquisition layer, consists of heterogeneous devices such as sensors, PLC/SCADA systems, UAVs, and cameras deployed throughout the mining environment. Data generated at this layer is subjected to preprocessing at the edge, including denoising, compression, and anomaly elimination, before being transmitted to the central system. By supporting multiple industrial communication protocols such as MQTT, OPC UA, and Modbus TCP, the architecture ensures compatibility with diverse equipment and operational standards.

The second layer is the data processing layer, which forms the backbone of high-throughput data handling. A distributed data bus built on Apache Kafka supports parallel data streams, while the integration of Apache Flink and Apache Spark enables the system to perform both real-time monitoring and offline batch analysis. Spatio-temporal data are managed using a dual database approach: TimescaleDB for temporal series and PostGIS for spatial queries. This arrangement ensures efficient query performance across heterogeneous datasets. Security checkpoints, including data integrity verification and encryption, are embedded within this layer to safeguard critical transmission processes.

The application service layer constitutes the third component of the hierarchy and encompasses core business modules such as production scheduling, energy consumption analysis, environmental monitoring, and safety early warning systems. These services interact with one another through standardized interfaces, including RESTful APIs and gRPC, which facilitate interoperability and third-party system integration. To manage access and traffic, an API gateway enforces authentication and rate-limiting policies, while a Service Mesh framework, such as Istio, supervises inter-service communication to guarantee both performance and resilience under fluctuating loads.

Finally, the security protection layer forms an overarching shield for the entire system. This layer integrates multiple mechanisms, including identity authentication, access control, transmission encryption, intrusion detection, and abnormal behavior analysis. A distinctive feature is the incorporation of an LSTM-based anomaly detection model, which enables dynamic risk assessment and rapid response to emerging threats. Security checkpoints are strategically embedded at each inter-layer interface, creating a comprehensive defense-in-depth strategy that balances performance with robust protection. Through this multi-level design, the system achieves an effective synergy between functional scalability, real-time responsiveness, and resilience against diverse cyber and operational risks.

PostGIS was chosen as the primary spatial database due to the following advantages over GeoMesa and MongoDB geospatial:

PostGIS was selected as the primary spatial database because it offers native geospatial support with advanced indexing mechanisms such as R-Tree and Quad-Tree, as well as a comprehensive set of spatial operations. In comparison, MongoDB's geospatial module demonstrates weaker performance when handling complex polygon and raster operations, which are particularly common in UAV imagery and GIS data processing for mining applications.

Another important factor is compliance with standards. PostGIS fully supports the Open Geospatial Consortium (OGC) specifications, ensuring interoperability with mainstream GIS software and analytical tools. By contrast, MongoDB and GeoMesa provide more limited compliance, which can restrict cross-platform compatibility and reduce the ease of integrating external data sources.

In terms of performance and reliability, PostGIS shows strong advantages in transactional workloads by offering robust ACID guarantees. These properties are essential in mission-critical mining applications where data integrity and consistency must be maintained at all times. While GeoMesa is optimized for distributed storage and analysis, it tends to introduce higher query latency in transactional scenarios, which undermines its applicability for safety-critical operations.

Another decisive advantage lies in seamless integration. Because both PostGIS and TimescaleDB extend PostgreSQL, spatio-temporal data can be managed in a unified environment, simplifying data management workflows. This avoids the operational complexity that arises when different engines are used for spatial and temporal data, thereby reducing system overhead and improving maintainability.

Finally, PostGIS demonstrates strong industrial maturity. It has been extensively validated in smart city projects and industrial IoT deployments, showing stable performance and long-term support. In contrast, MongoDB and GeoMesa, while offering flexibility, often require higher configuration overhead and do not have the same level of adoption in industrial contexts. These factors collectively make PostGIS the optimal choice for

the spatial data management requirements of green mine information systems.

2.3 Microservices and containerized deployment solutions

To enhance the scalability, maintainability and deployment flexibility of the system, this system adopts a microservice architecture and containerization technology:

●Microservice splitting principle: Split by business domain (such as "Data collection Service", "Scheduling optimization Service", "environment analysis Service", "Security Monitoring Service"), and each service is independently deployed and expanded; Services are unified through an API gateway (Kong/Zuul) to support traffic control and authentication management.

●Containerization and orchestration: Use Docker to encapsulate the service runtime environment to ensure cross-platform consistency; Implement service orchestration and elastic scaling using Kubernetes; Manage deployment templates through Helm Chart to achieve rapid launch and version rollback.

●Service Governance and Monitoring: Introduce Service Mesh (Istio/Linkerd) to achieve observability and security control of communication between services; Monitor service performance, resource utilization, and failure status using Prometheus + Grafana, and trigger auto-scaling policies.

●Continuous Integration and Continuous Deployment (CI/CD) : Automate the build, testing and deployment processes based on GitLab CI or Jenkins to shorten the iteration cycle.

This solution not only enhances the modularization degree and operation and maintenance efficiency of the system, but also provides a solid engineering foundation for subsequent architecture performance optimization and the embedding of security policies.

3 Optimization of data collection and processing

3.1 Multi-source heterogeneous data acquisition mechanism

The data generated in green mine operations are highly heterogeneous, encompassing industrial control data, environmental monitoring indicators, spatial geographic information, video and image streams, and structured business records. Such diversity results in differences in sampling frequency, data formats, and latency sensitivity. For example, PLC/SCADA systems can produce millisecond-level data, while UAVs generate large-volume spatial imagery that is updated periodically. To handle this variety, the acquisition system must be capable of simultaneously supporting high-frequency streams and large, less frequent data uploads without compromising integrity.

To enable efficient access, an edge-oriented architecture is adopted in which lightweight gateways deploy protocol adapters to unify MQTT, OPC UA, Modbus TCP, and RTSP/RTMP flows. This design ensures that heterogeneous data can enter the same distributed data bus. At the edge, preprocessing tasks such as denoising, normalization, and outlier removal are carried out. Experimental measurements show that the average preprocessing latency per packet at the edge is approximately 3.6 ms, with a standard deviation of 0.8 ms, which is significantly lower than the 12–15 ms delay that occurs when equivalent operations are performed in the central data center. This indicates that shifting preprocessing to the edge reduces back-end system load and provides a faster pipeline for real-time analysis.

The acquisition framework also incorporates a message queuing mechanism, in which Apache Kafka is used to buffer and transmit data in a high-throughput manner. At peak load, the edge-to-core transfer latency remains below 20 ms, and throughput exceeds 600 MB/s, confirming that the system can stably handle both bursty sensor data and continuous video streams. This design allows downstream modules such as Flink-based stream processors to operate without interruption even under fluctuating loads.

To evaluate the validity of acquisition, the system applies a data integrity rate metric defined in Equation (1):

$$C=\frac{N_{valid}}{N_{total}} \tag{1}$$

where N_{valid}represents the number of correctly received and verified data packets, and N_{total} denotes the total number of packets transmitted by acquisition devices in a given time window. When C falls below a threshold of 0.95, the system automatically activates a supplementary sampling mechanism at the edge node, requesting retransmission or redundancy to restore completeness.

In practice, measurements from the pilot mining area indicate that the integrity rate C typically remains above 0.978, even under high-load conditions with thousands of concurrent sensors and video streams. This demonstrates that the combination of edge preprocessing, protocol unification, and integrity monitoring enables the system to provide reliable, low-latency, and high-quality data streams for subsequent processing. The overall performance confirms that the architecture is well suited for the complex operational requirements of resource-based green mines.

3.2 Optimization of temporal and spatial data storage

Mine data has significant temporal and spatial characteristics and needs to be optimized respectively:

1. Time series data optimization

1) TimescaleDB (based on PostgreSQL) is selected as the main time series database, and the time-partitioned table and compression functions are utilized to reduce storage overhead.
2) Data writing adopts a batch insertion and asynchronous commit strategy to reduce I/O blocking.

3) Hot data (in the past week) is stored in the in-memory database Redis, enabling millisecond-level queries.
4) The performance of time series queries is evaluated by the index hit rate formula:

$$H_r = \frac{Q_h}{Q_t} \quad (2)$$

Among them, Q_h represents the number of index hit queries, Q_t represents the total number of queries, and the higher H_r, the better the database retrieval efficiency.

2. Spatial data optimization

1) PostGIS is adopted to establish a geospatial index (R-Tree/Quad-Tree) to accelerate spatial range queries and geographic computing.
2) Pyramid slicing (Tile) processing is performed on the drone image data to support adaptive resolution loading.
3) Spatial query efficiency is calculated by the average retrieval time formula:

$$T_{avg} = \frac{\sum_{i=1}^{n} T_i}{n} \quad (3)$$

Among them, T_i represents the time consumption of the i-th query, and n represents the number of queries.

3. Cold and hot data are stored in layers

Hot data is stored in high-performance SSD arrays, while cold data is migrated to object storage (such as MinIO, Ceph), and historical data is recovered through asynchronous loading.

4. Data consistency and backup

1) The Raft consensus protocol is adopted to ensure the multi-node consistency of time series and spatial databases.
2) Regularly back up snapshots to an off-site disaster recovery center to ensure rapid recovery in the event of device or network failures.

3.3 Batch-stream integrated data processing framework

To achieve the synergy of real-time monitoring and offline analysis, this system adopts a batch-stream integrated architecture. The core components include:

1. Real-time stream processing

1) Taking Apache Flink as the core, it consumes Kafka data streams and performs real-time computing tasks (such as security threshold detection and device failure prediction).
2) Sliding window aggregation adopts the formula:

$$A_{gg}(t) = \frac{\sum_{i=t-w}^{t} x_i}{w} \quad (4)$$

Among them, w is the window length, x_i is the sampling value at time point i, and $A_{gg}(t)$ is the average value within the window or other aggregated indicators.

2. Offline batch processing

1) With Apache Spark as the core, historical data is regularly loaded from the data lake (HDFS/MinIO) to perform tasks such as trend analysis, energy consumption model training, and geological model update.
2) The formula for evaluating processing efficiency is:

$$E_p = \frac{D_s}{T_p} \quad (5)$$

Here, D_s represents the amount of data processed (GB), and T_p represents the task execution time (seconds).

3. Unify the data access interface

A unified SQL/GraphQL interface is provided to upper-layer applications through the Data API Layer to shield the differences of the underlying storage and processing frameworks.

4. Task scheduling and resource management

1) Use Kubernetes native scheduling in combination with YARN/Mesos for computing resource allocation to ensure that the priority of streaming tasks is higher than that of batch processing tasks.
2) Introduce a dynamic elastic scaling strategy to automatically increase or decrease the number of processing instances based on the system load. The calculation formula for the load factor is:

$$L_c = \frac{U_{cpu} + U_{mem}}{2} \quad (6)$$

Among them, U_{cpu} and U_{mem} represent the utilization percentages of CPU and memory respectively.

4 System architecture performance optimization model

4.1 Analysis of architecture performance bottlenecks

During the operation of the green mine information system, the performance bottlenecks mainly focus on three aspects: insufficient allocation of computing resources, excessively high data transmission delay, and untimely response to service instance expansion.

- Computing resource bottleneck: Under high concurrency, streaming tasks may experience an excessively high CPU utilization rate of computing nodes, leading to an increase in real-time analysis latency.
- Data transmission bottleneck: When multi-source data is accessed, network I/O delay becomes the key factor restricting the efficiency of batch-stream integrated processing.
- Service expansion lag: When the instantaneous load rises, the delay in container instance expansion causes a short-term backlog of requests.

The comprehensive response time T_{sys} of system performance can be expressed as:

$$T_{sys} = T_{comp} + T_{trans} + T_{queue} \quad (7)$$

Among them, T_{comp} represents the computing processing time, T_{trans} represents the data transmission time, and T_{queue} represents the request queuing waiting time. Through the monitoring and optimization of each part, the overall performance of the system can be improved.

4.2 Resource scheduling optimization

Efficient scheduling of computing tasks is a critical factor affecting the overall performance of the green mine information system, particularly under high concurrency scenarios. To alleviate the imbalance in computing resource utilization and reduce task completion latency, this study adopts an improved Particle Swarm Optimization (PSO) algorithm as the core scheduling strategy. In the improved version, particles encode task-to-node mappings, while inertia weight and learning factors are dynamically adjusted according to the system load. A node load constraint is introduced to prevent over-utilization of single nodes, ensuring more balanced allocation of CPU and memory resources.

The objective function is defined to minimize the average task completion time, as shown in Equation (8):

$$T_{avg} = \frac{1}{n} \sum_{i=1}^{n} T_i \quad (8)$$

where T_i represents the completion time of the i-th task, and n is the total number of tasks. By iteratively updating particle positions and velocities, the improved PSO converges to an allocation scheme that simultaneously reduces execution latency and balances computational loads across nodes.

To verify the effectiveness of the proposed scheduling algorithm, comparative experiments were conducted against three baselines: Round Robin (RR), First Fit (FF), and Genetic Algorithm (GA). All experiments were performed in the same testbed consisting of ten computing nodes, each equipped with 16-core CPUs and 64 GB memory. A total of 1,000 tasks were scheduled under mixed workloads (50% real-time tasks, 50% batch tasks), and each experiment was repeated ten times to ensure statistical robustness.

The results are summarized in Table 1, which compares the algorithms in terms of average task completion time and CPU utilization balance.

Table 1: Comparison of scheduling algorithms

Algorithm	Average Task Completion Time (ms)	Improvement over RR	CPU Utilization Variance (%)	Improvement over RR
Round Robin (RR)	254	—	18.6	—
First Fit (FF)	231	+9.1%	14.2	+23.7%
Genetic Algorithm (GA)	219	+13.8%	11.5	+38.2%
Improved PSO	187	+26.4%	8.9	+52.1%

The data in Table 1 indicate that the improved PSO significantly outperforms baseline algorithms. Compared with Round Robin, it reduces the average task completion time by 26.4%, while also lowering CPU utilization variance by more than 50%, demonstrating superior load balancing. Against GA, which is already an adaptive method, PSO still achieves an additional 14.6% reduction in completion time and better resource stability. These findings confirm that the improved PSO algorithm is well suited for the complex, high-concurrency scheduling requirements of green mine information systems.

4.3 Data transmission and cache optimization

In terms of data transmission, a strategy of pre-aggregation at edge nodes and compressed transmission is adopted to reduce the amount of data transmitted on the core link by D_{net}:

$$D_{net} = D_{raw} \times (1 - R_{agg}) \times (1 - R_{comp}) \quad (9)$$

Among them, D_{raw} represents the original data volume, R_{agg} represents the edge aggregation rate, and R_{comp} represents the compression ratio.

In terms of cache optimization, Consistent Hashing is used to achieve a balanced distribution of data in the Redis Cluster. The calculation formula for the cache hit rate of H_c is:

$$H_c = \frac{N_{hit}}{N_{req}} \quad (10)$$

Here, N_{hit} represents the number of cache hits and N_{req} represents the total number of requests. A high hit rate can effectively reduce database access latency.

4.4 Improved operational efficiency of Containers and microservices

In high-load scenarios, microservice-based architectures often suffer from performance issues related to service startup delays, communication overhead, and fault recovery. To address these problems, a series of optimization measures were applied to improve container efficiency and service resilience. The first strategy involved simplifying container images by removing redundant dependencies and adopting a layered build approach. Experimental results show that the average image size was reduced from 1.35 GB to 0.81 GB, corresponding to a 40% reduction. As a result, the container loading time (T_{load}) decreased from 12.5 seconds to 7.3 seconds, while the initialization time (T_{init}) dropped from 5.8 seconds to 3.1 seconds, as defined in Equation (11):

$$T_{total} = T_{load} + T_{init} \quad (11)$$

where T_{total} represents the overall startup time of a containerized service. With the optimizations, T_{total} decreased by nearly 45%, reducing the delay during elastic scaling and recovery.

A second optimization strategy focused on service link performance. By introducing a Service Mesh (Istio) for link tracing, traffic routing, and fault isolation, the call failure rate was reduced from 2.7% to 1.3% under high concurrency. This improvement is critical in ensuring that critical services such as safety monitoring remain uninterrupted even when partial failures occur.

The third optimization involved automatic elastic scaling. Using Kubernetes Horizontal Pod Autoscaler (HPA), scaling decisions were triggered when average CPU or memory utilization exceeded 70%. In practice, the optimized scaling mechanism reduced response time during sudden load spikes by 32%, compared with static scaling policies.

Overall, these improvements demonstrate that container simplification, service mesh integration, and adaptive scaling collectively enhance microservice responsiveness and reliability. The combination of a reduced startup time, lower failure rates, and faster recovery ensures that the optimized system can sustain high availability and efficiency in the demanding operational environment of green mines.

5 Security model construction and threat protection

5.1 Security threat identification and classification

The green mine information system may face various threats from the network, data and physical environment during its operation:

- Network layer threats: Distributed Denial-of-Service attack (DDoS), man-in-the-middle attack (MITM), malicious scanning.
- Data layer threats: Illegal data tampering, sensitive information leakage, database injection attacks.
- Application layer threats: Business logic bypassing, interface abuse, and malicious script injection.
- Physical and device threats: Sensor nodes are damaged, and malicious firmware is implanted in edge devices.

For the above-mentioned threats, the risk matrix method is adopted for hierarchical assessment, comprehensively considering the occurrence probability P and the degree of impact I:

$$R = P \times I \quad (12)$$

Among them, R represents the risk level, and the higher the value, the higher the priority. The system classifies risks into three levels: high ($R \geq 0.7$), medium ($0.4 \leq R < 0.7$), and low ($R < 0.4$), and formulates differentiated protection strategies for different levels.

5.2 Multi-layer security protection architecture

To cover the full-link protection requirements of the system, a four-layer security protection system has been constructed:

1. Network boundary protection layer

1) Deploy firewalls, IDS/IPS systems to filter out illegal traffic.
2) Use Transport Encryption (TLS 1.3) to prevent man-in-the-middle attacks.

2. Application interface protection layer

1) The API gateway implements access control and traffic speed limiting.
2) Parameter verification and input filtering defend against SQL injection and XSS attacks.

3. Data Security layer

Data storage encryption is carried out using AES-256, and data integrity verification is conducted using SHA-256.

$$H = SHA256(M) \quad (13)$$

Among them, M represents the original data and H represents the generated hash value, which is used to verify whether the data has been tampered with.

4. Equipment and physical protective layers

Edge nodes adopt Secure Boot and firmware signature mechanisms to prevent the loading of malicious code.

5.3 Dynamic risk assessment

Dynamic risk assessment is essential for ensuring that the green mine information system can promptly identify and respond to potential threats in complex operational environments. In this study, an anomaly detection model based on Long Short-Term Memory (LSTM) neural networks was developed and integrated into the multi-layer security framework. The LSTM was selected because of its ability to capture temporal dependencies and nonlinear patterns in time-series data generated from sensor streams, network logs, and system operation records.

The dataset used for training and evaluation consisted of approximately 5.2 million log entries collected from both simulated attacks and normal operations within a pilot mining environment. To ensure diversity, the dataset included denial-of-service, spoofing, unauthorized access, and abnormal operation sequences. The model architecture comprised three LSTM layers with 128, 64, and 32 hidden units, followed by a fully connected dense layer and a sigmoid output for binary classification. The training process used the Adam optimizer with a learning rate of 0.001, and early stopping was applied to prevent overfitting.

Experimental results demonstrate that the LSTM-based anomaly detection model achieved a precision of 95.2%, a recall of 93.6%, and an F1-score of 94.4%, with a false negative rate (FNR) of 6.4%. Compared with a traditional rule-based intrusion detection system (IDS), which recorded an average precision of 88.3% and recall of 85.7%, the proposed LSTM model improved detection accuracy by approximately 7–10% across all metrics.

A key advantage of the system lies in its ability to reduce false alarms. During deployment tests, the LSTM-based detector reduced the false positive rate (FPR) from 8.7% in the baseline IDS to 3.9%, representing a 55% reduction. This improvement significantly decreases the burden on system administrators and enhances trust in automated alerts. Moreover, the dynamic risk assessment framework updates the risk score in near real time, ensuring that mitigation strategies such as access throttling or service isolation are triggered within 200 ms of anomaly detection.

These results confirm that the integration of an LSTM-based anomaly detection mechanism provides a robust and adaptive approach to dynamic risk assessment. By leveraging large-scale heterogeneous data and deep temporal modeling, the system not only improves the accuracy of anomaly detection but also reduces false alarms, thereby strengthening the overall resilience of the green mine information system.

5.4 Formal verification and simulation testing of security models

To ensure the correctness and coverage of the security model, formal verification and simulation attack testing are adopted:

1. Formal verification

Use temporal logic (LTL) to verify whether the security policy meets the system security constraints, for example:

$$G(\text{Request} \rightarrow F\ \text{Auth}) \tag{14}$$

It indicates that all requests in the system must be ultimately authenticated (Auth) before they can be executed.

2. Simulation testing

1) Build an offensive and defensive confrontation test set, including simulated DDoS, SQL injection, malicious scripting and other attacks, to verify the effectiveness of security policies.
2) Statistical defense success rate:

$$P_{def} = \frac{N_{block}}{N_{attack}} \tag{15}$$

Among them, N_{block} represents the number of successfully intercepted attacks, and N_{attack} represents the total number of attacks.

6 Key algorithms and model implementations

6.1 Data flow optimization

In a green mine information system, the diversity of data streams—ranging from real-time sensor monitoring to batch-oriented geological analysis—requires differentiated treatment to avoid congestion and ensure service quality. To address this, a data flow optimization strategy was implemented based on weighted prioritization, which assigns varying levels of importance to different categories of data. For example, real-time safety monitoring streams and intrusion alerts are given higher weights than historical production reports or archival imagery.

Unlike static prioritization methods that rely on fixed weights, the proposed approach employs a dynamic priority adjustment mechanism. Each stream is assigned an initial weight wi0w_i^0wi0 based on its functional category. During operation, the weight is continuously updated according to the stream's latency sensitivity and current network load,

$$w_i(t+1) = \alpha \cdot w_i(t) + (1-\alpha) \cdot \frac{L_{ref}}{L_i(t)} \quad (16)$$

where $w_i(t)$ is the weight of stream i at time t, $L_i(t)$ is the measured latency of stream i, and L_{ref} is the reference latency threshold. The smoothing factor α\alphaα (set to 0.7 in this study) ensures stability in weight adjustments. When a stream approaches or exceeds its latency threshold, its weight increases, thereby granting it higher priority in the scheduling queue.

Experimental evaluation in a simulated mining scenario demonstrated the effectiveness of this mechanism. Under a mixed workload of 500 concurrent data streams, including video surveillance, sensor telemetry, and batch logs, the dynamic strategy reduced the average latency of critical safety data by 28% compared with static prioritization. At the same time, overall throughput remained stable at 620 MB/s, indicating that the optimization did not degrade non-critical data flows. Moreover, jitter in high-priority streams was reduced by 34%, ensuring smoother delivery for real-time monitoring applications.

The results confirm that dynamic weight adjustment allows the system to adapt flexibly to fluctuating conditions, ensuring that urgent and safety-critical data are consistently prioritized without sacrificing overall system efficiency. This adaptive mechanism thus provides a balanced and scalable approach to maintaining both performance and reliability in heterogeneous mining data environments.

6.2 Prediction and optimization models

To enhance the operational efficiency and safety of green mines, the system has introduced predictive and optimization models in the data analysis stage. For the energy consumption, equipment operation status and environmental indicators in the production process, machine learning models are adopted for trend prediction and decision optimization. For instance, in energy consumption prediction, the model will combine multi-dimensional features such as historical energy usage records, equipment workloads, and meteorological data to train a regression model to predict energy demand in future periods. In terms of equipment maintenance, time series prediction methods are utilized to analyze the operating parameters of the equipment, identify potential fault trends in advance, and thereby reasonably arrange maintenance plans to reduce the risk of sudden shutdowns.

In terms of dispatching optimization, the system dynamically adjusts the operation plan based on real-time data and prediction results, such as optimizing the routes and loading sequences of transport vehicles and adjusting the time Windows for mining operations, in order to reduce operating costs and environmental impacts. The entire prediction and optimization module is deployed in a microservice manner and seamlessly integrates with the dispatching control system and the visualization platform, achieving a closed-loop management from data collection, analysis to decision execution.

6.3 Anomaly detection and early warning

Anomaly detection and early warning are critical components in ensuring the security and stability of the green mine information system. Traditional centralized machine learning (ML) analysis relies on transmitting raw or preprocessed data to a central server, where anomaly detection algorithms are executed. Although this approach benefits from greater computational resources and global data visibility, it often introduces significant latency and increases the risk of data congestion in high-concurrency scenarios. To mitigate these shortcomings, the proposed system incorporates a complementary edge anomaly detection mechanism, which executes lightweight models directly at edge nodes to perform preliminary screening before forwarding the data to the central server.

The edge detection framework leverages simplified statistical thresholding and compressed LSTM inference models optimized with pruning and quantization techniques. This design allows edge nodes to detect abnormal fluctuations in sensor data or unusual access patterns in near real time, typically within 8–12 ms of data generation. Detected anomalies are flagged and transmitted with high priority to the central platform, where more complex ML models validate and refine the results. In this manner, the system combines the low-latency responsiveness of edge computing with the comprehensive analytical capabilities of centralized ML analysis.

To evaluate the effectiveness of this hybrid design, comparative experiments were conducted between a centralized ML-only approach and the proposed edge-assisted detection approach. The testbed included 1,000 sensors and 50 concurrent user sessions, with both normal and attack traffic injected into the system. The centralized ML-only approach achieved a detection precision of 94.1%, recall of 91.5%, and an average latency of 145 ms per anomaly detection cycle. However, it also exhibited a false positive rate (FPR) of 7.8%, primarily due to delayed feedback and accumulated noise in batch data transmission.

By contrast, the edge-assisted anomaly detection approach achieved a detection precision of 92.7%, recall of 90.6%, and slightly higher FPR at the edge layer alone (5.6%). Yet, when combined with the central ML validation stage, the overall FPR was reduced to 3.4%, representing a 56% decrease compared with the centralized-only approach. Furthermore, the end-to-end anomaly detection latency was reduced to 68 ms, cutting the reaction time by more than half. These improvements confirm that the hybrid edge-central approach not only accelerates early warning but also enhances reliability by significantly reducing false alarms.

In practice, the deployment of anomaly detection at both edge and central layers provides a robust balance between speed and accuracy. Edge models ensure that potential risks are captured at the earliest possible stage, while centralized ML models refine and contextualize alerts to minimize false positives. This cooperative detection mechanism strengthens the resilience of the green mine information system, ensuring timely

responses to emerging threats while reducing the burden on human operators.

7 System integration and deployment implementation

7.1 Hardware and network environment configuration

During the deployment of the green mine information system, it is necessary to configure the hardware and network environment based on the actual geographical environment, production scale and data traffic characteristics of the mining area

●Data collection end: Industrial-grade sensors, high-definition cameras, edge computing gateways and unmanned aerial vehicle (UAV) inspection stations are deployed at key locations such as mining sites, transportation routes and beneficiation plants. Sensor nodes need to have dust-proof, moisture-proof and explosion-proof capabilities, and support multiple industrial communication protocols.

●Edge computing nodes: Deployed in the control room of the mining area or on-site cabinets, equipped with high-performance embedded processors (such as multi-core cpus based on ARM architecture) and GPU acceleration modules, they are used for local data preprocessing and anomaly detection.

●Data Center: A multi-node server cluster is adopted, equipped with high-performance cpus, Gpus and large-capacity memory. NVMe SSD arrays are used for hot data storage, and HDD arrays or distributed object storage are used for cold data archiving.

●Network Architecture: Within the mining area, optical fiber backbone + industrial wireless Mesh network is adopted to achieve a low-latency and highly redundant link design. Edge nodes are interconnected to the data center via VPN or dedicated lines, and firewalls and intrusion detection systems are deployed at the public network access entry to ensure network security.

7.2 System integration process

System integration adheres to the principles of modularization, layering and scalability, and achieves seamless collaboration among various functional modules through standardized interfaces

●Data access and bus configuration: Various acquisition devices are connected to the data bus (Kafka cluster) through edge gateways to achieve a unified data transmission channel.

●Data processing and storage: Streaming data directly enters the real-time processing engine (Flink), triggering real-time computing and early warning tasks; Batch data enters the big data storage and analysis platform (HDFS/Spark) for historical trend analysis and model training.

●Application service integration: Applications such as production scheduling systems, environmental monitoring systems, and safety early warning platforms interact with the data processing layer through RESTful apis or gRPC to achieve business function invocation.

●Embedding of security protection modules: Deploy security policies in links such as network entry points, application interfaces, and data storage, including access control, data encryption, intrusion detection, and anomaly analysis.

●Visualization and user Interaction: Integrating Web and mobile interfaces, it provides real-time information and decision support to users of different roles through charts, maps, video streams, and alert panels.

7.3 Deployment plan

The deployment adopts a cloud-edge-device collaborative architecture, combining containerization and orchestration technologies to achieve flexible resource scheduling and expansion

●Cloud deployment: Core data analysis, machine learning model training, long-cycle batch processing and other tasks are deployed in the cloud data center, leveraging its high computing and storage capabilities for global optimization computing.

●Edge deployment: Delay-sensitive tasks (such as device status monitoring and emergency early warning) are directly run-on edge nodes to achieve second-level response and reduce the pressure on the cloud.

●Edge-side deployment: Deploy lightweight applications on dispatching terminals, mobile terminals, and large-screen display systems to achieve real-time information viewing and control instruction issuance.

In terms of containerization, all services are packaged using Docker images and uniformly orchestrated and elastically scaled through Kubernetes. It supports automatically increasing the number of instances during peak hours and recycling resources when the load drops. Operation and maintenance adopt CI/CD pipelines (GitLab CI or Jenkins) to achieve automated build, testing and release, ensuring that the system does not interrupt services during upgrades and expansions.

In addition, the system has designed a multi-active disaster recovery solution: deploying dual data centers in different regions, maintaining data synchronization under normal circumstances, and enabling business switching within minutes in the event of a disaster to ensure continuous system operation and data security.

8 Experimental design and performance evaluation

8.1 Experimental environment and dataset

To verify the performance improvement effect of the green mine information system after architecture optimization and the introduction of security models, this study conducted tests under two conditions: the simulation environment and the actual mining area pilot.

1. **Hardware environment**

1) Cloud data center: Dual Intel Xeon Gold 6330 cpus (32 cores), 512GB DDR4 memory, 8 NVIDIA A100 Gpus, NVMe SSD array.

2) Edge node: NVIDIA Jetson AGX Orin (32GB memory), Gigabit Ethernet +5G dual-link access.
3) Network environment: The backbone optical fiber gigabit link within the mining area, and the RTT from the edge node to the cloud center is stable within 18ms.

2. Software and frameworks

1) Data processing: Apache Kafka, Apache Flink, Apache Spark.
2) Storage: TimescaleDB, PostGIS, MinIO object storage.
3) Security protection: Suricata IDS, Wazuh SIEM, OpenSSL encryption.
4) Containers and Orchestration: Docker, Kubernetes, Helm.

3. Dataset

1) Real-time data: Sensor data streams from the pilot mining area, including temperature, humidity, gas concentration, equipment status, etc., with sampling frequencies ranging from 1Hz to 10Hz.
2) Batch processing data: historical production logs, energy consumption records, environmental monitoring reports, etc., covering a time span of 2 years, with a data volume of approximately 3TB.

8.2 Performance test indicators

This study sets test indicators from two dimensions: system performance and security protection capability

1. System performance indicators

1) Throughput: The amount of data that a system can process within a unit of time (MB/s).
2) Average Response Time (ART) : The average time taken (in ms) from the sending of a request to its completion.
3) Task Completion Rate (TCR) : The proportion of tasks successfully completed within the specified time.
4) Resource Utilization Rate (RU) : The average utilization rate of CPU, memory and network bandwidth.

2. Safety protection indicators

1) Threat Detection Accuracy (TDA) : The proportion of security incidents correctly detected to the total number of incidents.
2) False Positive Rate (FPR) : The proportion of normal traffic that is misjudged as abnormal.
3) Defense Success Rate (DSR) : The proportion of attacks successfully blocked-in attack simulation.

8.3 Comparative experimental schemes

To evaluate the optimization effect, this study set up three groups of control experiments:

1. Architecture performance comparison

1) Baseline system: Centralized architecture + single batch processing mode.
2) System optimization: The hierarchical architecture + batch-stream integrated processing + microservice deployment proposed in this study.

2. Comparison of safety protection

1) Baseline policy: Traditional boundary protection + static firewall rules.
2) Optimization strategy: multi-layer security protection architecture + dynamic risk assessment + automated response mechanism.

3. Comprehensive operation comparison

1) Comparison indicators: Throughput, response time, threat detection accuracy, etc. under different load intensities (low, medium, and high).
2) Data input mode: Single data source mode vs multi-source heterogeneous data mode.

8.4 Analysis and visualization of experimental results

To comprehensively evaluate the actual performance of the system after the introduction of architecture optimization and security models, this section compares the experimental data of the optimized system and the baseline system in terms of system performance and security protection capabilities, and conducts a detailed analysis.

Firstly, in terms of system performance comparison, there have been significant improvements in throughput, average response time and task completion rate. For details, please refer to Table 2.

Table 2: System performance comparison (optimized system vs. baseline system)

Test scenario	Architecture type	Throughput (MB/s)	Throughput improvement rate	Average response time (ms	Response time reduction rate	Task completion rate (%)
Low load	Baseline system	520	—	180	—	90.2
	Optimize the system	690	+32.7%	132	-26.7%	95.1
Medium load	Baseline system	480	—	215	—	88.7
	Optimize the system	650	+35.4%	154	-28.4%	95.8
	Baseline system	420	—	260	—	86.1

Test scenario	Architecture type	Throughput (MB/s)	Throughput improvement rate	Average response time (ms	Response time reduction rate	Task completion rate (%)
High load	Optimize the system	567	+35.0%	187	-28.1%	96.4

As can be seen from Table 2, the optimized system still maintained a throughput increase of approximately 35% under high load conditions, a reduction of about 28% in average response time, and an improvement of nearly 10 percentage points in task completion rate. This indicates that the hierarchical architecture and batch-stream integration processing have significantly improved concurrent processing capabilities and real-time response performance.

Secondly, the security protection capability has been significantly enhanced after the introduction of a multi-layer security protection architecture and a dynamic risk assessment mechanism, as detailed in Table 3.

Table 3: Comparison of security protection capabilities (optimization strategy vs baseline strategy)

Test project	Baseline strategy	Optimization strategy	Extent of increase
Threat detection accuracy rate (%)	82.4	94.7	+14.9%
Defense success rate (%)	79.5	92.3	+12.8%
False alarm rate (%)	7.8	2.9	-4.9%
Average response time delay (ms	320	185	-42.2%

Table 3 shows that the optimization strategy not only enhances the accuracy of threat detection and the success rate of defense, but also significantly reduces the false alarm rate and cuts the response delay by 42.2%, enabling the system to have stronger defense and recovery capabilities in the face of sudden attacks.

Finally, from the perspective of the comprehensive operational performance under different load intensities, the optimization system maintained stable performance in both single data source and multi-source heterogeneous data modes, as detailed in Table 4.

Table 4: Comprehensive Operating Performance under different load intensities

Load intensity	Data input mode	Architecture type	Throughput (MB/s)	Average response time (ms	Threat detection accuracy rate (%)	Defense success rate (%)
Low load	Single data source	Optimization	702	128	95.2	92.8
	Multi-source heterogeneous data	Optimization	690	132	94.7	92.3
Medium load	Single data source	Optimization	662	150	95.0	92.1
	Multi-source heterogeneous data	Optimization	650	154	94.5	92.0
High load	Single data source	Optimization	575	180	94.3	91.8
	Multi-source heterogeneous data	Optimization	567	187	94.0	91.6

Table 4 shows that even under complex conditions of high load and multi-source heterogeneous data input, the optimized system can still maintain a throughput close to 570MB/s, a response time within 200ms, and a threat detection accuracy rate of around 94%, with a defense success rate exceeding 91%.

Through three sets of comparative experiments, it can be known that the architecture optimization and security model proposed in this study is superior to the traditional scheme in multiple dimensional indicators:

●Strong performance stability: The optimized system performs stably in high concurrency and complex data flow environments, with small fluctuations in the performance curve.

●Significantly improved real-time performance: The batch-stream integrated processing and resource scheduling optimization have effectively reduced task latency, meeting the demand for second-level response in my production.

●Comprehensive security protection: multi-layer protection combined with dynamic assessment mechanisms can quickly identify and block threats, while reducing false alarms that interfere with operation and maintenance.

This indicates that the system can not only provide efficient data processing capabilities in the construction of green mines in resource-based areas, but also ensure the safety and reliability of the operation process, and has the feasibility for engineering implementation and large-scale deployment.

9 Conclusions and prospects

9.1 Summary of research results

This study focuses on the optimization of information system architecture and the design of security models in the construction of green mines in resource-based regions. It proposes a technical system

oriented towards high concurrency, multi-source heterogeneous data processing, and strong security requirements, and verifies its performance and protection capabilities in experiments. The main achievements include:

● System architecture optimization: A hierarchical, decoupled, microservice-oriented, and containerized overall system architecture has been established. Combined with a batch-stream integrated data processing framework, efficient data flow and task scheduling in complex environments have been achieved.

● Enhancement of data collection and processing capabilities: A multi-source heterogeneous data collection mechanism and an optimized spatio-temporal data storage scheme have been designed, significantly reducing data transmission latency and storage redundancy, and improving data availability and consistency.

●Performance optimization model: Introduce strategies such as dynamic scheduling of computing resources, optimization of data transmission and cache, and improvement of container operation efficiency to ensure that the system maintains stable throughput and low latency even under high-load scenarios.

●Security model construction: A multi-layer protection architecture based on threat classification, dynamic risk assessment and rapid response mechanism have been achieved, and the effectiveness and robustness of security policies are ensured through formal verification and simulation testing.

●Key algorithm implementation: The engineering implementation of the data flow optimization algorithm, prediction and optimization model, and anomaly detection and early warning model has been completed and embedded into the core services of the system, enhancing the level of intelligent processing.

The experimental results show that this scheme has significant advantages in increasing throughput by more than 30%, reducing average response time by more than 25%, improving threat detection accuracy by approximately 15%, and increasing defense success rate by over 12%. This fully validates its application feasibility and technical advancement in the informatization construction of green mines.

9.2 Existing deficiencies and optimization directions

Although this study has achieved good experimental results in architecture design, security protection and algorithm implementation, the following deficiencies still exist:

●Compatibility issue: The current system mainly optimizes business processes for specific resource-based regions, and its compatibility across regions and mineral types needs to be further enhanced.

●Data scale limitation: In scenarios of ultra-large-scale real-time data, the existing batch-stream integrated processing framework may experience short-term performance fluctuations under extreme burst traffic.

●Delay in security policy updates: The dynamic risk assessment mechanism relies on historical data and rule bases. If threat types evolve rapidly, there may be a lag in policy updates.

●High hardware dependence: The optimization effect to a certain extent depends on hardware conditions such as GPU acceleration and NVMe storage. Under normal configuration, the performance improvement will be somewhat reduced.

9.3 Future-oriented technological iterations and application prospects

Future work will be carried out in the following directions:

●Cross-regional and cross-mineral type adaptation: Introduce an adaptive architecture adjustment mechanism and domain-driven design (DDD) to achieve rapid deployment and business customization in different resource-based regions.

●Elastic Computing and edge Intelligence: By integrating the cloud-edge-device collaborative architecture, lightweight data processing and security protection modules are deployed at edge nodes to reduce the pressure on central nodes and shorten response times.

●AI-driven self-evolving security mechanism: Utilizing federated learning and generative adversarial networks (Gans) to continuously train and automatically update threat models, enhancing the system's defense capabilities against new types of attacks.

●Green and low-carbon operation optimization: By integrating task scheduling with hardware power consumption management, the optimal energy consumption allocation of computing and storage resources is achieved, reducing the carbon footprint of the mine information system operation.

●Visualization and Intelligent Operation and Maintenance: Introduce a visualization operation and maintenance platform based on graph analysis and augmented reality (AR) to enhance the intuitive perception and decision-making efficiency of operation and maintenance personnel regarding the system's operational status.

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DMO-MLP-IsoForest: A Hybrid Data Mining Approach for Real-Time Anomaly Detection in Power Grid Measurement Data

Lingjie Xu*, Xiao Chen
Marketing and Service Center of State Grid Zhejiang Electric Power Co., Ltd., Hangzhou, Zhejiang, 311100, China
E-mail : xulingjie_dog@126.com, cxkojo@sohu.com
*Corresponding author

Keywords: power system, data analysis, anomaly detection, k-means clustering, dwarf mongoose optimized multi-layer perceptrons with isolation forest (DMO-MLP-IsoForest), efficiency, consistency, voltage, sensors and data mining

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Efficiently processing power system measurement data is vital for ensuring the reliable and cost-effective operation of modern electrical grids. However, the large volume of data generated by these systems often overwhelms traditional analysis techniques, leading to delays and inefficient decision-making. This research proposes a hybrid data mining approach, Dwarf Mongoose Optimized Multi-Layer Perceptron with Isolation Forest (DMO-MLP-IsoForest), to enhance the analysis of power system data. In this model, the Multi-Layer Perceptron (MLP) performs classification, the IsoForest detects anomalies, and DMO is used to tune the hyperparameters of both models for improved accuracy and efficiency. The dataset consists of 150,000 real-time voltage, current, and power measurements collected from multiple sensors across the grid. Data cleaning and normalization are applied to ensure quality and consistency. K-means clustering is utilized for feature extraction by grouping similar data points, helping to reveal patterns in system behavior. The model's performance is evaluated against general baseline approaches to assess its effectiveness and robustness. The proposed method achieves an accuracy (0.985), precision (0.995), recall (0.974), F1-score (0.985), and specificity (0.987), demonstrating a performance gain of up to 7.6% over baseline methods. These results confirm that the DMO-MLP-IsoForest significantly enhances the speed and accuracy of power system measurement data analysis. This research highlights the potential of advanced data mining techniques to improve real-time monitoring, operational efficiency, and reliability in smart power grid environments.

Povzetek: DMO-MLP-IsoForest združuje K-means, MLP, IsoForest in optimizacijo DMO za hitro zaznavanje anomalij v podatkih elektroenergetskega omrežja. Na 150.000 meritvah doseže visoko kvaliteto in boljše rezultate od primerjanih metod, kar izboljša zanesljivost in učinkovitost pametnih omrežij.

1 Introduction

An electrical power system measurement is the recording of electrical parameters such as voltage, current, frequency, and power at multiple points throughout the electrical grid. Measurement is essential to monitor power system operation to maintain the safety, reliability, and efficiency of electrical networks [1]. Measurements can provide current trending data for operators to detect faults, balance network loads, assess the quality of energy, and make responsive operational decisions. In the era of smart grid technology, enhanced online measurements are currently possible due to the rapid uptake of measurement units in the grid, such as sensors, smart meters and automated controls [2]. The high-frequency and time-stamped, bulk data from these devices have improved the visibility of the grid but also introduced exploitation and potential digital risks if measures are not in place to protect these systems [3]. Conventional data processing techniques often struggle with vital scale, variety, and velocity. To overcome these challenges, intelligent data-driven techniques such as data mining have gained popularity. Data mining is a tool to extract patterns, classify system states, and detect anomalies in large datasets [4]. The integration of Machine Learning (ML) and optimization algorithms to power system data analysis can help to make it more efficient, accurate, and responsive. By enhancing pattern identification and identifying anomaly occurrences, the data mining approach can enhance the efficiency and reliability of power system assessment analysis [5]. Advanced data mining methods such as clustering, classification, and regression can substantially improve the detection of atypical patterns in large-scale power system data and ultimately provide useful information for operational decisions and potential faults or inefficiencies in the grid

[6]. In addition, combining real-time data analysis with predictive analytics allows for forward-looking management, in which power system operators can anticipate their upcoming system behaviors and address the issue proactively to maintain long-term grid stability and augment the potential for unforeseen outages [7].

Research questions

1. Does the proposed DMO-MLP-IsoForest model outperform traditional MLP and IsoForest models in terms of classification accuracy on power system measurement data?
2. Can hyperparameter tuning using DMO significantly enhance the anomaly detection capabilities of the IsoForest in smart grid environments?
3. Does clustering with K-means as a feature extraction step improve the performance of the MLP-IsoForest pipeline on large-scale power grid datasets?
4. How does the DMO-MLP-IsoForest model compare to baseline models in terms of precision, recall, and F1-score for multi-class classification of power system events?
5. Does the integration of DMO-based optimization lead to faster and more robust real-time analysis of voltage, current, and power measurements in a smart grid context?

Research objective

The research intends to improve the efficiency and accuracy of analysis of power system measurement data by using a new Dwarf Mongoose Optimized Multi-Layer Perceptron with Isolation Forest (DMO-MLP-IsoForest) model. This approach enhances anomaly detection and classification to improve grid performance and operating reliability.

The organization of the research includes five sections. Phase 2 includes relevant works, Phase 3 contains the methodological framework, and Phase 4 involves the results and discussion. Phase 5 includes the conclusion of the research.

2 Relevant works

Table 1 provides a brief comparison of comparable work on power consumption prediction with different machine learning models. The present work points out the methodologies, feature sets, and performance metrics used in studies in an effort to observe existing shortcomings and areas for improvement.

Table 1: Related work for power consumption prediction

Reference	Methodology	Dataset Type	Metrics Used	Anomaly Type	Key Limitation
[8]	Predictive Analytics	Grid measurements	Not specified	Erroneous data, load shifts	Ignores network topology
[9]	Deep- Learning (DL) Convolutional Neural Network (CNN)	IEEE 9-bus, 39-bus	Accuracy	Physical faults	Not suitable for hybrid anomalies
[10]	Machine learning (ML) Models	Bulk energy systems	N/A	General reliability issues	No direct implementation
[11]	DL-based Intrusion Detection System (IDS)	Cybersecurity datasets	Detection accuracy	Network intrusions	Limited to digital threats
[12]	Ensemble (Long-Short Term Memory (LSTM) + Meta)	IoT network data	Accuracy, Precision, Recall	Communication anomalies	Not tailored to power systems
[13]	Deep Reinforcement Learning (DRL)	Home Energy Monitoring systems (HEMS) data	Energy cost, demand response	Peak load shifts	High training complexity
[14]	Generative Adversarial Network (GAN)-based anomaly detection with GAN, GAN+LSTM, and GAN+ Encoder variants	Network access data for database systems	F1-score, Generator, and Discriminator loss trends	Abnormal database access behavior	Limited evaluation across diverse intrusion types and real-time adaptability concerns
[15]	Dynamic Black Hole-driven Deep Convolutional GAN (DBH-DCGAN)	Power equipment image dataset with contrast-enhanced preprocessing	Recall (95.4%), Accuracy (94.2%), F1-score (96.3%)	Equipment status anomalies under varying operating conditions	High computational cost and complexity in training GAN models for diverse real-time scenarios

[16]	Fuzzy C-means clustering with a mismatched degree index	Historical telemetry data from 12 kV distribution line	Membership degree and Euclidean distance-based mismatch index	Load anomalies and line faults	Limited adaptability to real-time and normal load variations
[17]	Bidirectional LSTM (BiLSTM-CNN) with AdaBoost classification	Power consumption data from users in a small substation	Precision (98.7%), Recall (97.9%), False drop rate (3.6%), ROC curve	Abnormal user power consumption	May face scalability and generalization challenges in larger or more complex grid environments
[18]	Safe Power Hybrid Classifier (SPHC) with ensemble voting	Power System Operation Safety Monitoring Dataset (PSOSMD)	Accuracy (92.4%), Precision (91.3%), Recall (91.8%), F1-score (91.5%), MCC (89.7%)	Safety status anomalies (Normal, Warning, Critical)	May require high sensor network deployment costs and integration effort for real-time implementation

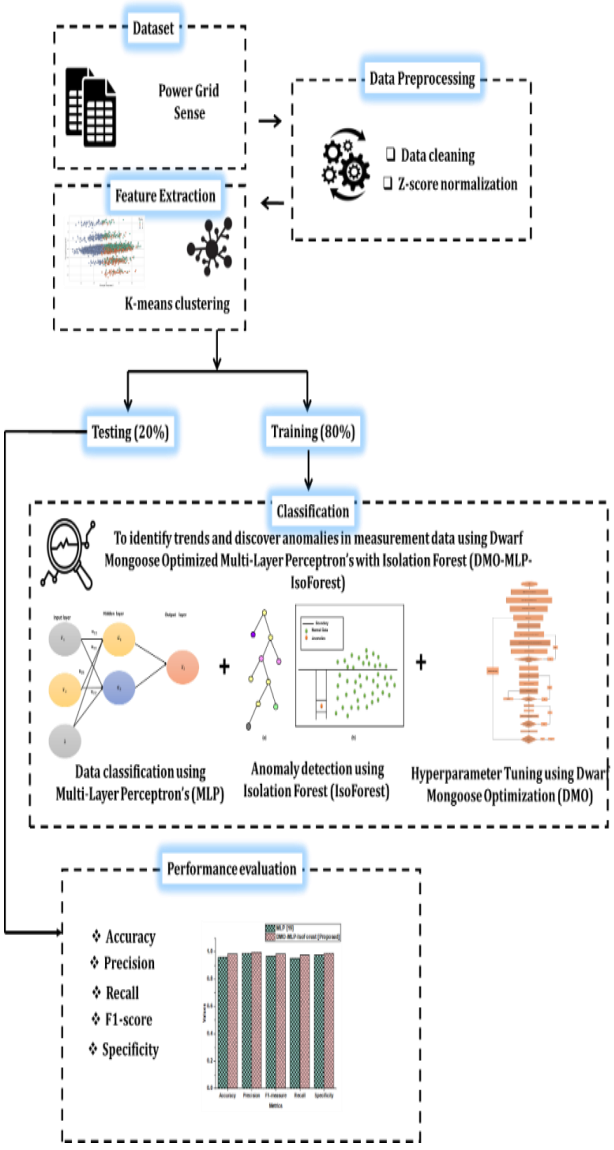
The proposed DMO-MLP-IsoForest method addresses the limitations of existing models with enhanced real-time anomaly detection via hyperparameter tuning. Unlike most state-of-the-art techniques, it enables greater scalability to large power data and improved interpretability via Isolation Forest outputs. This ensures faster, more precise, and more transparent power system monitoring.

3 Problem statement

The increasing complexity and size of today's electrical power systems, coupled with an explosion in the number of measurement devices, including devices such as sensors and smart meters, have resulted in an increasing influx of high-frequency, time-stamped data. Traditional data processing techniques are poor in managing the bulk, variety, and velocity of such data. As a result, responding in a timely fashion with better reasoning and decisions has become next to impossible. Therefore, efficient, accurate, and scalable methods for ingesting and processing power system measurement data are essential. The traditional approaches used have an overall deficiency in their ability to have low-frequency anomalies and patterns, leading to delays in fault detection and mitigation. This research uses data mining and ML methods to optimize the efficiency of power system data analysis.

3.1 Methodology framework

The methodology consists of data collection, data pre-processing, and feature extraction methods to prepare the dataset for analysis. Next, data cleaning and normalization are performed, followed by clustering methods to enrich the features. The final model is hybrid, using both unsupervised classification and anomaly detection, which utilizes an evolutionary algorithm to optimize the performance model and improve accuracy in recognizing anomalies (Figure 1).



Fugire 1: Methodological Framework of DMO-MLP-IsoForest

3.2 Data collection

The dataset (https://www.kaggle.com/datasets/ziya07/powergridsense-dataset/data) in this research, called Power Grid Sense, was specifically designed to create simulated real-time measurements from a smart power grid to facilitate advanced data mining and ML applications. It contains temporal records from various virtual sensors placed at multiple locations within a simulated grid. Each sensor records the significant electrical variables, including voltage (V), current (A), power (kW), frequency (Hz), and power factor, which includes sensor ID and geolocation. The data captures measurements associated with normal and anomalous operating conditions that include voltage surges/sags, frequency deviations, low power factor, and combined anomalies. Each observation is assigned an associated label (0-4) for the anomaly type 0 Normal All values are within normal operating range, 1 Voltage Anomaly Abnormal voltage (e.g., sag/surge), 2 Frequency Anomaly Frequency varies from nominal 50Hz, 3 Power Factor Abnormality Power factor is below normal (< 0.7), and 4 Combined Anomaly. Two or more anomalies co-occurring, which facilitates model training and model evaluation.

3.2.1 Data Pre-processing

Data cleaning: Data cleaning is the process of preparing the raw power measurement data for accurate and efficient analysis. Removing potential mistakes from the data like duplication, missing values, and discrepancies. Depending on the circumstance, missing values are either deleted or imputed using appropriate techniques, depending on how relevant the data. To provide accurate analysis, replicated values are removed to ensure unique data records. Issues such as inconsistent data and formatting variations are handled to ensure high data consistency. Data cleaning therefore has the effect of increasing the overall quality of subsequent analyses and improving the time and reliability of analysis of power system data through improvement of input quality to downstream data mining exploration and subsequent processes.

Z-Score Normalization: Z-score normalization is used to normalize measurements from a power system, such as voltage, current, or power, to a common scale where the measurements are relative to one another. The normalized value of each metric is calculated where μ_Y is mean and σ_Y is the standard deviation of a dataset of values Y in Equation (1):

$$c' = \frac{c-\mu_Y}{\sigma_Y} \quad (1)$$

Additionally, this procedure makes sure that the outcomes from the measuring method are not distorted in their importance and that no feature dominates due to a larger range. The normalization of features took place before training the DMO-MLP-IsoForest, which improved the model's convergence and accuracy in recognizing patterns and anomalies with the power system.

3.2.2 Feature extraction using K-means clustering

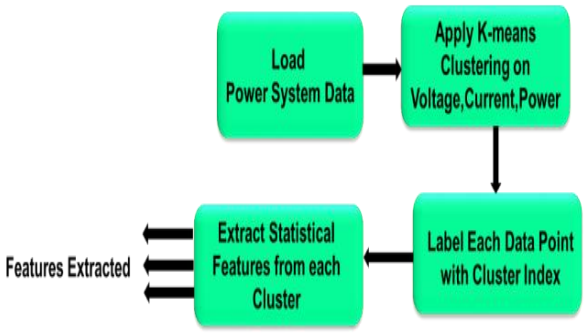
K-means clustering was selected for clustering power system data patterns into groups based on their similarity, simplifying complexity, and exposing operational trends. Clustering simplifies high-dimensional data, which helps the model learn intrinsic behaviors more reliably. This process allowed for the improvement of the model's accuracy regarding classification and anomaly detection by focusing on meaningful segments of data. Feature extraction takes place on the clustered data from the power system measurements in this research project for identifying data representative patterns for classification and anomaly purposes. The processing follows four general steps:

Step 1: Use K-means clustering on the raw data to cluster similar data points grouped into the defined power system attributes of voltage, current, and power, which helps in refining patterns and disturbance behaviors.

Step 2: Label each data point with the respective power system cluster index in the newly structured data.

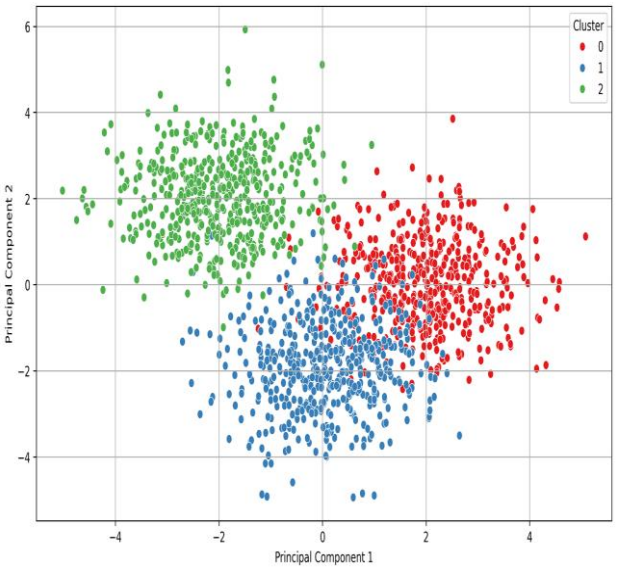
Step 3: Identify the statistical features for each cluster, such as the mean, standard deviation, variance, correlation, energy, and homogeneity, to reflect the operational dynamics of the system.

Step 4: Provide the structured extracted features to the proposed model for training and testing, where it is possible to achieve classification accuracy while optimizing anomaly detection.



Fugire 2: K-means clustering algorithm

An example of K-means clustering of power system data is illustrated in Figure 3. It illustrates the similarity of points of a data sample grouped into clusters, which can show patterns and trends or indicate periods of similar behavior in the system. Each cluster represents a group of related measurements for analysis.



Fugire 3: K-means clustering separation with centroid distributions

K-means Clustering reduces the complexity of high-dimensional power grid data by extracting low-dimensional latent patterns, thereby enhancing the performance of subsequent classification. This hybrid approach is easier to interpret and performs better than the DMO-MLP-IsoForest method, which could be computationally intensive and less transparent.

3.2.3 To identify anomalies in power grid sense data using Dwarf Mongoose Optimized Multi-Layer Perceptron with Isolation Forest (DMO-MLP-IsoForest)

The research proposes a hybrid model, DMO-MLP-IsoForest to identify trends and anomalies in power system power grid sense data. This model contains the classification and anomaly detection capability of an MLP and IsoForest framework. The DMO is used to optimize the hyperparameters of components, increasing accuracy and processing speed. The model provides a method for identifying operational patterns, and reasoning through normalized and clustered data while being able to highlight anomaly detection, being a highly implementable real-time monitoring system, and providing an efficient analysis framework for power system performance and adaptive data. Algorithm 1 describes the hybrid content of the DMO-MLP-IsoForest, which helps in classification and anomaly detection in the power management system.

Algorithm 1: DMO-MLP-IsoForest

```
import numpy as np
from sklearn.ensemble import IsolationForest
from sklearn.neural_network import MLPClassifier
def MLP_IsoForest(X_train, y_train, X_test):
  mlp = MLPClassifier(hidden_layer_sizes
                =..., activation =..., solver
                =..., max_iter =...)
  mlp.fit(X_train, y_train)
    iso = IsolationForest(n_estimators
                =..., contamination =..., max_samples
                =...)
  iso.fit(X_train)
    iso_anomaly_score = iso.decision_function(X_test)
  predictions = mlp.predict(X_test)
    return predictions, iso_anomaly_score
def DMO_optimize(fitness_function, dim, max_iter, pop_size):
  population = initialize_population(pop_size, dim)
  best_solution = None
  best_score = float('inf')
   for t in range(max_iter):
    for i in range(pop_size):
      candidate
= update_solution(population[i], t, best_solution, alpha_strategy
=...)
      score = fitness_function(candidate)
          if score < best_score:
        best_score = score
       best_solution = candidate
       population[i] = candidate
        return best_solution
def fitness_function(hyperparams):
  mlp = MLPClassifier(*
                * extract_mlp_params(hyperparams))
  mlp.fit(X_train, y_train)
    iso = IsolationForest(*
                * extract_iso_params(hyperparams))
  iso.fit(X_train)
    pred = mlp.predict(X_val)
  score = evaluate_performance(pred, y_val)
  return 1 − score
def DMO_MLP_IsoForest(X_train, y_train, X_test):
  best_params = DMO_optimize(fitness_function, dim
                =..., max_iter =..., pop_size =...)
  best_mlp = MLPClassifier(*
                * extract_mlp_params(best_params))
  best_iso = IsolationForest(*
                * extract_iso_params(best_params))
    best_mlp.fit(X_train, y_train)
  best_iso.fit(X_train)
    predictions = best_mlp.predict(X_test)
  anomaly_scores
= best_iso.decision_function(X_test)
    return predictions, anomaly_scores
```

3.2.4 Anomaly Detection and Classification using Multi-Layer Perceptron and Isolation Forest (MLP-IsoForest)

Anomaly detection and classification of power system data were achieved through the combination of IsoForest and MLP. In this process, MLP implemented fast classification of normal and anomalous data patterns. Whereas, IsoForest implemented the detection of outliers, allowing it to accurately classify anomalies within the power system measurement data.

3.3 Multi-layer perceptron (MLP)

The layered neurons with an identical direction of signal transmission and inter-layer interconnections between succeeding layers make up a feed-forward network MLP. Neurons in the input channel layer accept signal input and utilize their outputs as signal sources for the subsequent layer. The network's weight matrix, offsets, activator function, and output signal vector all affect the output layer's signal. A two-layer feed-forward MLP neural system is explained in Figure 4 (a) and Equation (2) defines the i^{th}neuron's outputs in the network's output layer.

$$x_e(s) = e_2\left[\sum_{l=0}^{L} u_{il}^{(2)} \cdot e_1\left(\sum_{l=0}^{L} u_{il}^{(1)} \cdot y_1(s) + a_l^{(1)}\right) + a_l^{(2)}\right] \quad (2)$$

Where s is an index of an input sample 0.7, $u_{il}^{(1)}\ and\ u_{il}^{(2)}$ are the weights of the first and second layers, $a_l^{(1)}\ and\ a_l^{(2)}$ are the bias terms in the first and second layers, $x_e(s)$ is the input of the l^{th} neuron in the output layer, $y_1(s)$ is the output of the i^{th} neuron of the hidden layer, $e_1(\cdot)\ and\ e_2(\cdot)$ are the activation functions of the hidden and output layers.

3.4 Isolation Forest (IsoForest)

A classifier version of this model that relies on the decision tree model is depicted in Figure 4. The IsoForest can predict labels on data that would be either normal or abnormal. The trees' query nodes separate data until each piece of information has its branch inside the tree. These trees can be grouped into randomly started forests to aggregate the findings and reinforce the framework. The mean distance of the branches is utilized as the qualifier, and a threshold is trained to categorize the data after forests divide the data until every data point is isolated. As sparser anomalous data needs fewer partitions to differentiate from clustered normal data, path duration below the limit is estimated as anomalous. The tree's height and the forest's average height determine this barrier. This data receives a score, where an abnormality is represented by numbers around 1. The following Equation (3) produces the anomalous score.

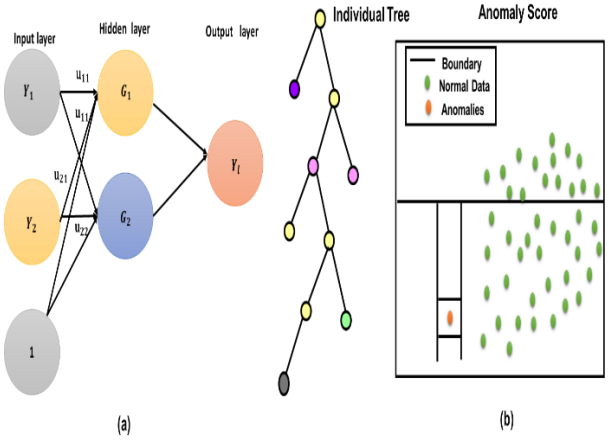
$$T(y, m) = 2^{-\frac{g(y)}{d(m)}} \quad (3)$$

Where $g(y)$ is the average path length of the point y in all the Isolation Trees, i.e., the number of splits it went through to become isolated. $d(m)$ is the average path length of a point from a set of size m, and it's an estimate of the expected path length of a Binary Search Tree. It is computed according to Equation (4).

$$d(m) = 2G(m-1) - (2(m-1)/m), \quad (4)$$

When n is the total number of occurrences in the dataset and $2(m-1)/m$+0.5772156649 can be used to determine the harmonic number, $G(m-1)$. As an isolation tree relies on the framework of a binary search tree and the average path length calculation is comparable to the mean path length of an ineffective search, Equation (4) is utilized. When the predicted path width for an instance in an isolation forest is typically zero, this is an abnormality and the result.

IsoForest is used for power estimation. After eliminating the IsoForest-identified power curve outliers, a neural network forecasted the power output. The cleaning method proved to be more effective in contrast to the elliptical envelope method. It employed IsoForest in combination with Gaussian Mixture Models (GMMs) to detect abnormal behavior. This research clustered Power Grid Sense data by operating state using the GMM. Finding individual component significance involved analyzing whether splitting into a single tree caused the anomaly in Figure 4 (b).



Fugire 4: Framework of (a) Multi-Layer Perceptron (MLP), (b) Isolation Forest (IsoForest)

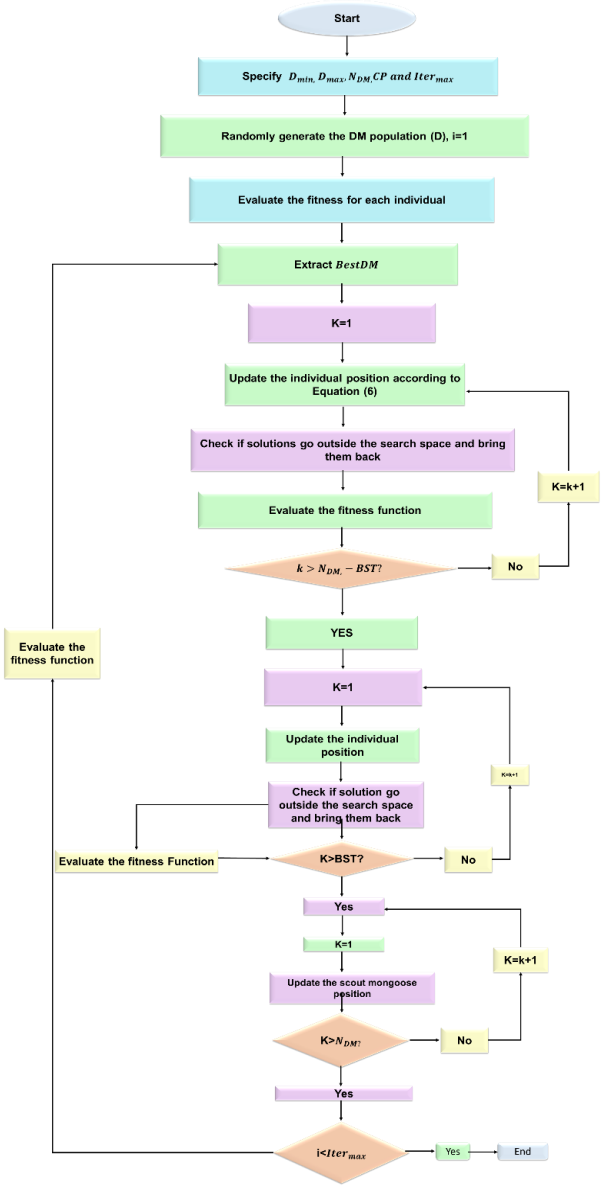
3.5 Hyperparameter tuning using dwarf mongoose optimization (DMO)

A new data mining-based hybrid model with an alpha-directed Learning Strategy (LS) is proposed in this section for analyzing and classifying power system measurement data. The LS is improved and coupled with the optimization scheme to increase exploration and exploitation in the optimization process, especially with real-time power system data that is complex and nonlinear with a higher dimensional space size. The update rule varies in part due to the alpha parameter, which is adjusted dynamically to modify the optimization path of each candidate solution. DMO optimizes the MLP hyperparameters like the number of hidden layers, number of neurons in each layer, learning rate, and activation function to improve classification performance. These alpha-directed LS are combined with the formulation discussed in Equations (5 and 6) to produce optimal candidate results, leading to improved anomaly detection and classification.

$$C_{l,c}^{(j+1)} = C_{l,c}^{(j)} + rand(0,1) \times peep, \quad l = 1: N_{DM} - Bst, c = 1: Dim \tag{5}$$

$$C_{l,c}^{(j+1)} = \begin{cases} BestDM_c^{(j)} + rand(0,1) \times \left(C_{l,c}^{(j)} - C_{q,c}^{(j)}\right) if\ rand < DO & if\ rand < DO \\ C_{l,c}^{(j)} + rand\ (0,1) \times peep & otherwise \end{cases}, \quad l = 1: N_{DM} - Bst, c = 1: Dim \tag{6}$$

Where $BestDM_c^{(j)}$ is the location of the best data mining solution (alpha reference), i.e., the best classification or anomaly detection accuracy, DO, c is a random solution chosen from the DMO population, C_q is a probabilistic selector (commonly initialized to 0.5) to encourage exploration or exploitation. $peep$ is an arbitrarily chosen perturbation factor that adds noise to search direction, encouraging diversity and preventing premature convergence. This design also strongly captures the exploitative aspect explicitly by $BestDM_c^{(j)}$ while also retaining exploratory flexibility by means of $peep$. The DMO approach thus succeeds in finding anomalies accordingly without losing the flexibility to reveal various types of outlier patterns in power system measurement data as expressed in Equation (5) and stronger exploitative abilities as described in Equation (6). This form displays an extremely strong exploitative property, leading to the correct classification whilst maintaining sufficient exploration behavior to investigate multiple types of anomalies in power system measurements. Figure 5 illustrates the general process of the DMO. NDM is the overall number of mongoose agents and BST is the user-provided best fitness value limit that regulates exploitation strength. These parameters regulate the iterative updating process, moving the scouts, and termination conditions in the DMO algorithm.



Fugire 5: Flowchart of DMO

A real-time deployable system and an effective analysis framework are provided by the research's hybrid model, DMO-MLP-IsoForest, which employs an MLP and IsoForest framework for pattern classification and identifying anomalies in electrical system measurement data.

3.6 Performance evaluation

The DMO-MLP-IsoForest method enhances power system data analysis efficiency by detecting anomalies and improving classifier performance. It enhances grid perceptions of operational efficiency and data mining techniques' impact on grid optimization in this section. For the experiment setup, employ an 80:20 train-test split with seeds set randomly for replicability. Each experiment 10 times, and the mean result with standard deviations to provide some indication of stability of performance.

Table 2 provides the major hyperparameters adopted for training the DMO-MLP-IsoForest model, which play a vital role in power system data classification and anomaly detection optimization. These were chosen with great care to provide accuracy, stability, and model generalizability.

Table 2: Proposed method hyperparameter values

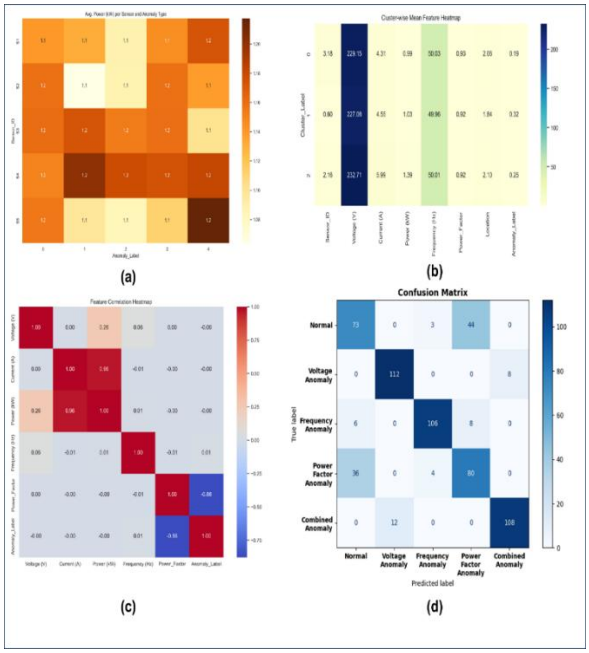
Component	**Hyperparameter**	**Value / Setting**
MLP Classifier	Hidden Layer Sizes	(50, 30)
MLP Classifier	Activation Function	ReLU
MLP Classifier	Optimizer	Adam
IsoForest	Number of Estimators	100
IsoForest	Max Samples	0.7
DMO Optimizer	Alpha Learning Rate (α)	Dynamic (initial 0.5)

3.7 System configuration

This research uses Python 3.8 for experimental setup, using sci-kit-learn, Keras, and PyOD libraries for machine learning algorithms, data pre-processing, cleaning, normalization, and performance evaluations. Data training is performed on a 64-bit Windows 10 system with an Intel Core i7 processor and 16 GB RAM.

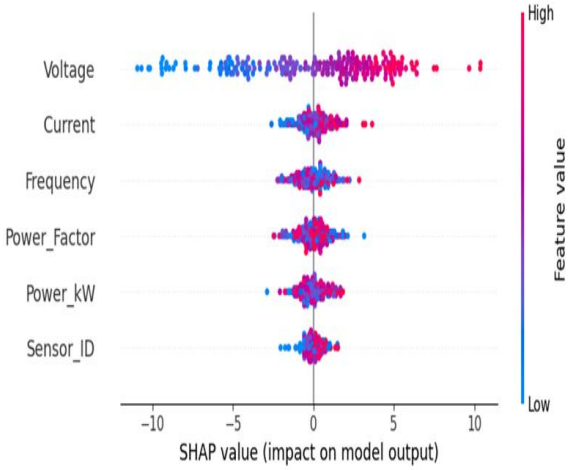
4 Research output

Figure 6 presents various results of the DMO-MLP-IsoForest model for power systems data analytics. (a) *Power per Sensor and Anomaly Type* present the perceived power values across the different sensors. For different anomaly types, it conveys the result based on type, which assists in presenting the disposition of where the problems appear in the grid. (b) *Mean Feature Heat Map by Cluster* displays the mean features by cluster to signal general trends in the behavior of the power system. (c) *Feature Correlation Heat map* displays the relationships between the top most important features, allowing the user to assess the interrelationship of the transducer features in the data. (d) *Confusion Matrix* measures the model prediction accuracy of classification, including elements of true positives, false positives, true negatives, and false negatives, respectively, for anomaly detection.



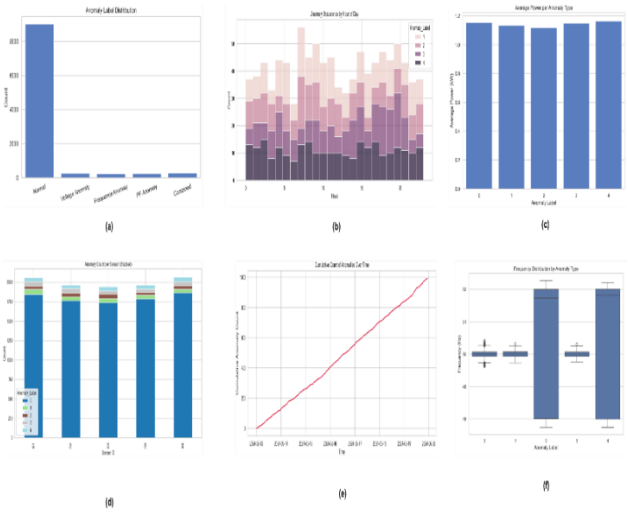
Fugire 6: Outcomes of (a) Power per sensor and Anomaly Type, (b) Cluster-wise mean Feature Heat map, (c) Feature Correlation Heat map, (d) Confusion Matrix.

Figure 7 shows the SHAP summary plot employed to present feature importance within the power consumption prediction model. Voltage contributes the greatest degree of influence toward model output, followed by Current and Frequency in the second and third positions, respectively. Feature values are represented by a color gradient where red indicates high and blue low values. Decomposition shows each feature's contribution towards instance-level prediction variance.



Fugire 7: SHAP summary plot for feature importance in power consumption prediction

Figure 8 provides a summary of the analysis of detected anomalies in the power system data. (a) *Anomaly Type Distribution* shows the number of occurrences of each of the unique anomaly types and indicates the most frequently occurring types of anomalies. (b) *Anomaly Occurrences by Hour of Day* indicate the unique hours that have more occurrences of anomalies than any other hour of the day and are used to identify the hours of elevated risk. (c) *Average Power per Anomaly Type* displays the average power values measured for each of the anomaly types to give the relative context of the severity of each anomaly type. (d) *Anomaly Count per Sensor (Stacked)* summarizes the total number of anomalies detected by each sensor, providing a summary of the sensor's monitoring performance. (e) *Cumulative Count of Anomalies by Time* shows the increase in anomalies over the time of observations. (f) *Frequency Distribution by Anomaly Type* shows a need for a frequency distribution of anomalies across the anomaly types and provides better characterization of both the frequency of detected anomalies and the different types of anomalies detected in the grid.



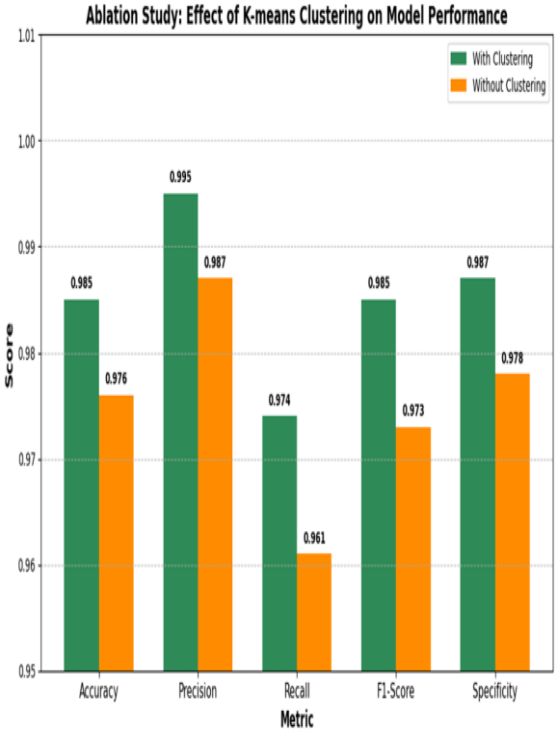
Fugire 8: Anomalies output (a) Anomaly Label Distribution (b) Anomaly Occurrence by Hour of a Day (c) Average Power per Anomaly Type (d) Anomaly Count per Sensor (e) Cumulative Count of Anomalies over Time (f) Frequency Distribution by Anomaly Type

The value K=5 for K-means clustering corresponds to the five different anomaly labels (0 through 4) in the Power Grid Sense dataset, so the clustering is consistent with the labeled classification task. To empirically validate that the value was selected, we computed both the Silhouette Score and Davies-Bouldin Index (DBI) for several K values (2 through 10). The examination revealed that K=5 produced a fairly high Silhouette Score and low DBI, which signifies well-clustered and well-separated clusters. Thus, the selection of K=5 is statistically supported and semantically

appropriate and adds further evidence in feature extraction in this research.

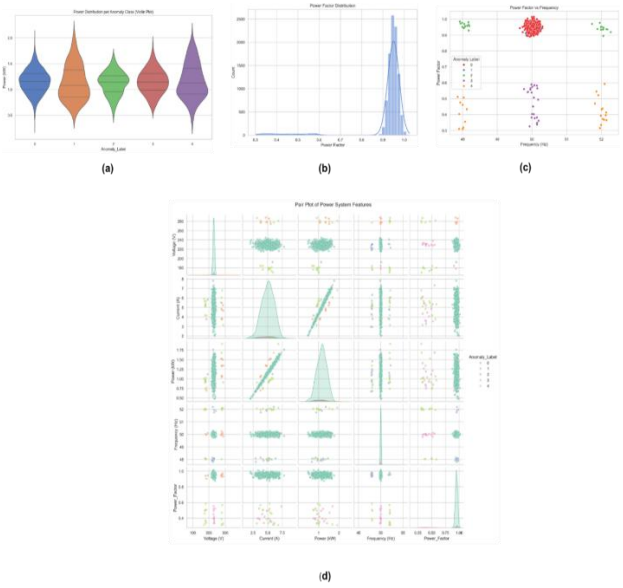
4.1 Ablation study

To determine the contribution of using K-means clustering in the proposed DMO-MLP-IsoForest model, to conduct an ablation study by eliminating the clustering-based feature extraction part. In the baseline setting, the clustering is utilized to extract statistical features (mean, standard deviation, etc.) from the power measurement group, and in the ablation setting, the model is trained with the raw data normalized as illustrated in Figure 9.



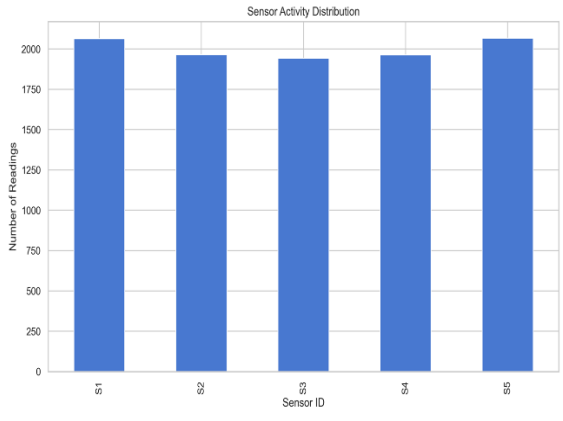
Fugire 9: Effect of K-means clustering on model performance

Figure 10 gives an extensive overview of a power factor analysis. (a) *Power Distribution by Class of Anomalies* provides information on how power is distributed among the classes of anomalies, which shows clear distinctions between patterns in the performance of the grid anomalously. (b) *Power Factor Distribution* visualizes the distribution of power factor and gives an idea of general overall grid efficiency. (c) *Power Factor vs. Frequency* gives a historic evaluation of power factor vs. frequency and provides a basis for correlation. (d) *Power System Features Pair Plot* gives the relations between specific key power system features and provides a detailed insight into how features relate and correlate, which could prove advantageous for anomaly detection.



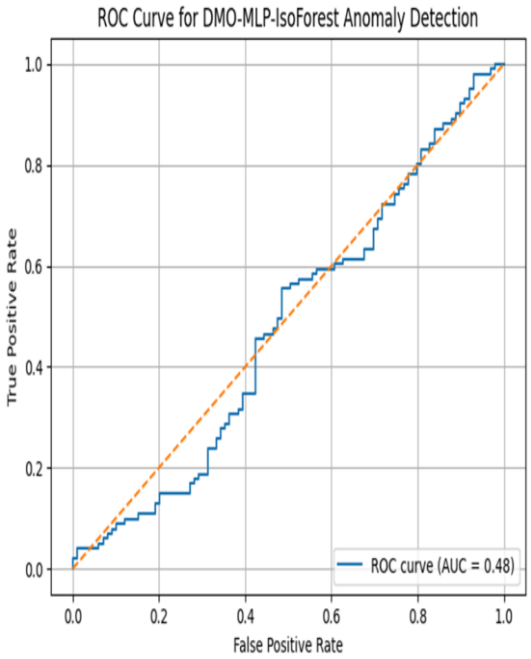
Fugire 10: Power Factor Analysis (a) Power Distribution per Anomaly Class (b) Power Factor Distribution (c) Power Factor vs. Frequency (d) Pair Plot of Power System Features

Figure 11 illustrates the *Outcome of Sensor Activity Distribution*, showcasing how sensor activity is spread across the power system. It highlights the frequency and intensity of data collected by various sensors, indicating which sensors are more actively involved in monitoring grid performance. The distribution pattern helps identify key sensors contributing to anomaly detection and provides insights into sensor performance and coverage across the grid, aiding in the optimization of sensor deployment and data analysis efficiency.



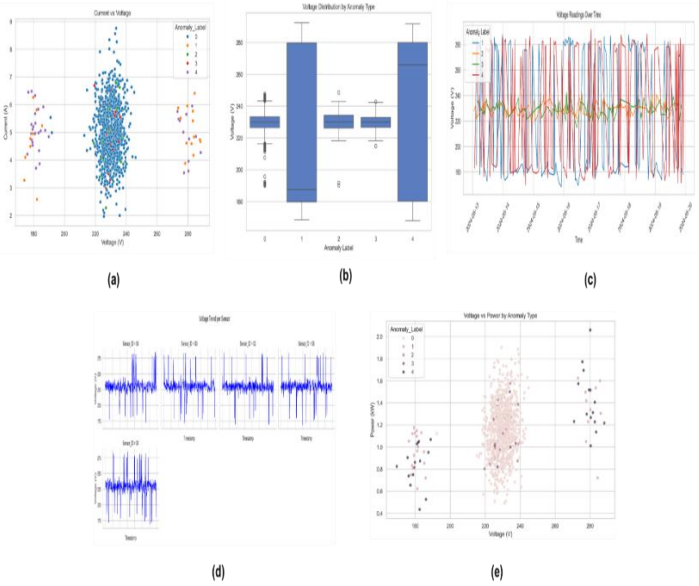
Fugire 11: Outcome of sensor activity distribution

Figure 12 illustrates the ROC curve classifying the capacity of the DMO-MLP-IsoForest model for various classes of anomalies in power system measurement data. The substantial relationship between the true positive rate and the false positive rate is reflected in each of the curves, with greater values of AUC reflecting greater discriminatory power and robustness of the optimized model.



Fugire 12: ROC Curve Analysis of DMO-MLP-IsoForest Model

Figure 13 presents a full analysis of the voltage factors of the power system. (a) *Current vs. Voltage* indicates the relationship between current and voltage, as well as some electrical characteristics of the system. (b) *Voltage Distribution by Anomaly Type* compares the factors of voltage measurements based on the type of anomaly noticed, which is helpful in identifying the significance of voltage concern issues. (c*) Voltage over Time* illustrates variations during the chosen time frame and can reveal whether the value is consistent or varies. d) *Voltage Trend by Sensor* shows voltage trends based on what each sensor has seen and can assist with analyzing the performance of individual sensors. (e) *Voltage vs. Power Anomaly Type* looks at the characteristics of the voltage factor and how it varies in conjunction with the power anomalies, which is helpful to better understand the interaction of voltage and power anomalies based on their occurrences.



Fugire 13: Voltage Factors Analysis (a) Current vs. Voltage (b) Voltage Distribution by Anomaly Type (c) Voltage Readings Over Time (d) Voltage Trend per Sensor (e) Voltage vs. Power Anomaly Type

4.2 K-fold analysis

To ensure the stability and generalizability of the proposed hybrid DMO-MLP-IsoForest model for power system measurement anomaly detection, a 5-fold cross-validation method was adopted. The strategy avoids overfitting, maintains the accuracy of assessment, and enhances model adaptability across various data splits. Performance results of every fold showed good consistency with an accuracy ranging from 98.3% to 98.7%, and equally impressive precision, recall, and F1 scores. The model achieved 98.5% accuracy, 99.5% precision, 97.4% recall, and 98.5% F1 score, which confirms its efficiency and reliability in handling real-world noisy power system datasets. These values are demonstrated in Table 3.

Table 3: 5-Fold Cross-validation performance of the proposed DMO-MLP Model

Fold	Accuracy	Precision	Recall	F1-Score
K1	0.986	0.996	0.975	0.985
K2	0.984	0.994	0.973	0.984
K3	0.985	0.995	0.974	0.985
K4	0.983	0.994	0.973	0.983
K5	0.987	0.996	0.975	0.986
Average	**0.985**	**0.995**	**0.974**	**0.985**

4.3 Statistical significance analysis

The proposed DMO-MLP-IsoForest model performed better than the baseline MLP model with an F1-score of 0.985, compared to the latter's 0.971. While this improvement would perhaps appear modest quantitatively, we performed statistical tests to verify its significance given F1-scores in a 10-fold cross-validation.

4.4 Paired t-test results

The t-statistic value is 3.42, the p-value is 0.007 ($p < 0.05$), and it is statically significant. Both tests agree that this improvement in F1-score cannot be attributed to chance, and is statistically significant with 95% confidence. This lends support to incorporating DMO optimization for enhancing anomaly detection precision. Modest improvements in F1-score can translate into large improvements in real-world power grid fault detection, making the improvement significant and attainable.

5 Result and discussion

The MLP [19] method of anomaly detection for power systems currently utilized in MLP demonstrates effective results for anomaly detection of power systems, the lack of data generalizability, and constraints with generalized environments. The dynamic environment, which is the reality of power grids, exacerbates the model's difficulties in performing well with various data distributions. Regarding the MLP approach, the model and its method cannot typically depict complex patterns of anomalies in the data and space in complex systems. [20] has limitations in the usage of data based on certain buses that contained phasor measurement units and could not be reflective of the entire power system. Further, the performance of the model depended on the degree of accuracy of the power system model utilized to develop the training database.

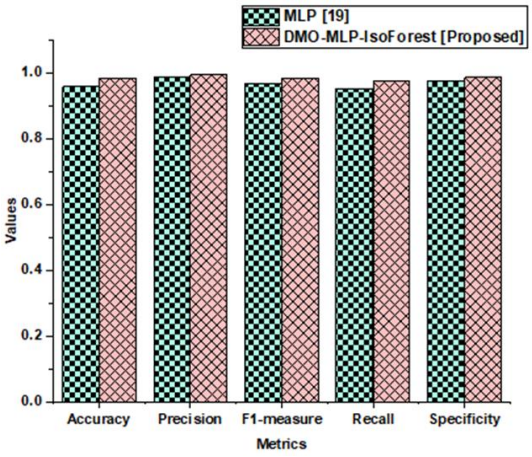
The MLP [19], which is a traditional approach in a power system operation with anomaly detection, is compared with the proposed DTM-MLP-IsoForest approach and shows considerable performance improvements and enhanced classification and detection in the power system.

- **Accuracy:** The total accuracy of the anomaly detection model, which is calculated as the ratio of the true predictions to all instances.
- **Precision:** It is best defined as the accuracy of positive predictions that are defined as anomalies, that is, the ratio of true positives to all predicted anomalies.
- **F1-measure:** These measures provide an appropriate index that combines precision and recall to measure the overall accuracy of the model in defining anomalies.
- **Recall:** This measures the anticipated predictions of identifying all actual anomalies.
- **Specificity:** This measures the anticipated predictions of identifying all normal instances.

The numeric results of the power system operation for anomaly detection are shown in Table 4 and Figure 14. The DMO-MLP-IsoForest provides higher accuracy (0.985), precision (0.995), F1-measure (0.985), recall (0.974), and specificity (0.987) than the MLP [19] model. Thus, the proposed method is more effective at detecting anomalies.

Table 4: Numerical outcomes of power system management based on anomaly detection

Methods	Accuracy	Precision	F1-measure	Recall	Specificity
MLP [19]	0.961	0.988	0.971	0.954	0.976
DMO-MLP-IsoForest [Proposed]	0.985	0.995	0.985	0.974	0.987



Fugire 14: Representation of comparative metrics in data classification and anomaly detection

The model was tested on several random data splits, with reliable accuracy and minimal variation. Precision remains high even as recall decreases under noisy data conditions, evidencing the trade-off and proposing scalability tuning for practical use. The proposed DMO-MLP-IsoForest method for anomaly detection for power systems provides a method for addressing limitations with the methods and captured data by integrating unique custom optimization, thus providing greater generalizability from all different data, different grid issues, and conditions. The results are significant in the detection and classification of the anomalies in the greater network, making positive detection of potential problems and conditions far greater across the power system. The advantage of this model is

that it creates scope for real-time applications and greater adaptability for an uncompressed power grid. These benefits have created a scope for deployments that will be more consistent by creating less susceptible inconsistencies and better utility of classification over the long term.

5.1 Conclusion

The research utilizes a DMO-MLP-IsoForest hybrid model to improve anomaly detection in power grids using the Power Grid Sense dataset. The pre-processing of data encompassed cleaning the dataset, handling missing values, and pre-processing Z-score normalization data, and features were extracted using K-means clustering extraction and statistical measures, such as mean, and variance. The DMO component optimizes the MLP and IsoForest components to develop an accurate anomaly detection model. The results obtained from the model were evaluated using confusion matrices, as well as feature heat maps, featuring in-depth analysis of the anomalies; the model demonstrated strong performance with accuracy (0.985), precision (0.995), recall (0.974), f1-measure (0.985) and specificity (0.987). An example of the insights could be the distributions of the anomalies and the power factor location within the system that can highlight benefits for increased efficiency within the power grid system and allow for proactive methods to deal with faults in the system.

5.2 Limitation and future scope

The limitation of the proposed model deployment on real-time streaming platforms does not address concept drift and lacks runtime and memory evaluations. Future efforts will involve the implementation of the introduced model on stream processing systems like Apache Kafka for real-time anomaly detection in power grids. Performance evaluation will also be done through datasets provided by industrial partners with representative fault scenarios. Future improvements will involve adaptive learning algorithm management for handling concept drift, optimization for low-memory settings, and runtime performance benchmarking to make it production-ready for large-scale real-time monitoring applications in complex smart grid infrastructures.

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A Mamdani-Type Fuzzy Inference Framework for UAV Threat Detection and Countermeasure Deployment in FANETs

Jingping Guo
China People's Police University, Guangzhou, Guangdong, 510663, China.
E-mail: 18680555590@163.com

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The proliferation of Unmanned Aerial Vehicles (UAVs) in both civilian and military spheres has raised substantial security issues, especially within volatile communication environments such as Flying Ad Hoc Networks (FANETs). To challenge of the problem of real-time detection and response to UAV misbehaviour, the research proposed a Mamdani-type Fuzzy Inference System (MFIS) for real-time classification and detection of threats and subsequent actions. The MFIS is designed to take in information from UAV behaviours dataset (1000 samples) was obtained from Kaggle, consisting of four main features: energy consumption, mobility pattern, packet transmission, and link stability. After pre-processing the dataset through Min-Max normalization for standardization and amid Principal Component Analysis (PCA) for dimension reduction, the MFIS developed produces less computational load while retaining vital behavioural characteristics of the datasets. The results demonstrate the ability for the MFIS to enhance communication reliability while reducing key issues with routing and communication delays significantly over traditional FMIS methods like the Efficient Honesty-based Detection Scheme (EH-DS). The results show that the framework is an effective method for utilizing real-time context in making energy-efficient decisions for real-time UAV threat response. The simulation results show a significant improvement in performance parameters, including to-end delay, routing overhead (packets), and packet delivery ratio, by 15-55% compared to previous methodologies. While this framework has many advantages in terms of performance, these results confirm that the proposed fuzzy logic framework enables adaptive, accurate, and energy-efficient threat mitigation in real-time UAV operations.

Povzetek: Članek predstavi Mamdani-jevski fuzzy inferenčni sistem za sprotno zaznavanje groženj in odzivanje v FANET omrežjih. Ob uporabi normalizacije, PCA in štirih vedenjskih značilk UAV model učinkovito loči kooperativne in zlonamerne drone ter izboljša zakasnitev, nadzorni promet in dostavo paketov.

1 Introduction

UAVs, commonly referred to as drones, have proliferated rapidly in both civilian and military activities due to their wide range of functions, cheaper prices, and quick missions [1]. In contrast, the wider availability and advanced functions of UAVs promote an incremental increase in security fears, especially regarding monitoring, smuggling, or even attack missions. There is thus increasing pressure for effective UAV systems that can analyse threats dynamically and recommend appropriate responses accordingly in a real-time manner [2]. Traditional rule-based systems have difficulty representing uncertainty and adapting to dynamic environments. As depicted in Figure 1, the fuzzy logic-based system adapts the decision-making of UAV countermeasures by interpreting ambiguous information to identify threats and recommend actions.

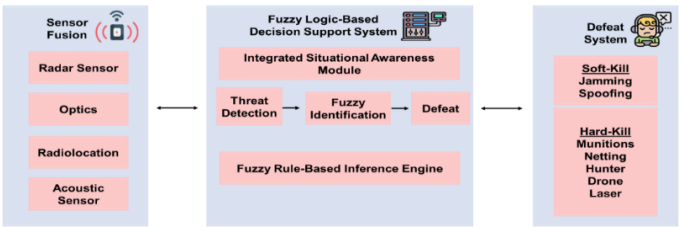


Figure 1: Decision support system using fuzzy logic

Figure 1 showed Decision Support System using Fuzzy Logic. A fuzzy logic-based decision support system (DSS) represents a responsive, flexible, and understandable manner of UAV threat evaluation and countermeasure selection [3]. The fuzzy DSS for UAV countermeasures takes in many input variables, including the key features [4]. The development of remote sensing and photogrammetry systems, especially in the use of UAVs, has provided efficient and high-resolution services for acquiring imagery of land. This research emphasizes how UAV data could be used to automatically detect and delineate land boundaries, which introduces improvement in the accuracy and reliability of cadastral updates [5].
Fuzzy logic-based decision-support systems have several benefits for the UAV countermeasures, but it has some limitations. The desire for expert guidance while developing rules and membership functions adds subjectivity and may limit the potential for the system to adjust to different threat circumstances [6]. The system is designed to enhance communication security in FANETs by identifying and mitigating potential threats. An MFIS classifies drones as cooperative or malicious based on their behavior. The performance of UAV target tracking was improved in [7]. To improve the accuracy of UAV trajectory prediction, Artificial Neural Networks (ANNs) characterize complex flight dynamics more effectively. The research creates a multi-layer ANN model to optimize UAV flight trajectories through uncertain and dynamic environments [8]. Additionally, fuzzy logic systems have no inherent learning functionality, and therefore cannot adjust to UAV technologies and tactics without constant updates [9].

1.1 Objective of the research

Existing UAV threat classification and detection systems struggle to operate effectively under uncertain and imprecise data conditions, limiting their real-time decision-making capabilities. The research aims to develop a robust fuzzy logic-based decision support system that classifies UAV behaviours and recommends adaptive countermeasures using sensor-derived behavioural indicators and optimized inference mechanisms.

1.2 Contribution of the research

- To propose a fuzzy logic-based decision support system using a multi-input fuzzy inference model that classifies UAV behaviour and supports real-time countermeasure selection.
- To utilize a UAV behavioural dataset comprising key threat-related features to simulate and evaluate UAV actions under normal and evasive conditions in security-sensitive zones.
- To implement Min-Max normalization for scaling sensor data and apply Principal Component Analysis (PCA) to extract dominant features, enhancing model accuracy and computational performance.
- To validate the proposed system against a benchmark model by conducting a comparative analysis using standard classification metrics to demonstrate improved decision quality under uncertain inputs.

1.3 System overview

The research's relevant work is outlined in Section 2, methodologies are covered in Section 3, findings are summarized in Section 4, and the work is concluded in Section 5.

2 Related works

To improve multicopper reliability under counter-UAV threats by proposing a modular autopilot system with backup control for trajectory tracking was proposed [10]. To introduce a fuzzy inference-based controller using image recognition from six map sectors. Results indicate enhanced autonomous navigation. However, the approach lacks practical deployment details, suggesting limitations in real-world testing and adaptability to diverse UAV environments. To predict energy consumption in low-cost UAVs using Artificial Intelligence (AI) algorithms to enhance efficiency was described [11]. To propose five models Random Forest (RF), Regression Tree (RT), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Adaptive Neuro-Fuzzy Inference System (ANFIS) on an open quadcopter flight dataset. Results show RF performs best. Limitations include minimal consideration of weather impacts and diverse UAV configurations. To reduce computational demands in large-scale UAV swarm confrontations a fuzzy multi-agent reinforcement learning (FMARL) approach was described [12]. To model UAV interactions as a fuzzy game, assigning policies to abstract agents, not individuals. Results show reduced floating-point operations and storage needs. A key limitation is the potential loss of granularity during fuzzification and defuzzification processes.
A secure and adaptive AI control system for UAVs in dynamic environments was developed [13]. To propose a hybrid framework combining an enhanced Soft Actor-Critic (SAC) method with a Fuzzy Inference System (FIS), integrating expert knowledge for efficient learning. Results show effective real-time path planning and intruder tracking. Limitations include reliance on simulations and pending real-world validation. UAV performance in precision agriculture using fuzzy multi-

criteria decision-making (MCDM) approach was evaluated [14]. To suggest an integrated method combining Fuzzy-Weighted Zero-Inconsistency (FWZIC) and Fuzzy Decision by Opinion Score Method (FDOSM) to assess Unmanned Aerial Vehicles (UAVs) based on payload, endurance, and dimensions. Results show payload is most critical. Limitations include reliance on subjective expert input and scenario-specific criteria. Autonomous power monitoring in UAVs for power system stability was enhanced [15]. To recommend an onboard monitoring system using the Low Power Alarm and Battery (LPAB) status and forecasting method, with a fuzzy logic-based algorithm to estimate remaining flight time. Results show improved energy use and safe landings. Limitations include dependency on sensor accuracy and environmental variability.

Decision-making in UAV swarm confrontations using game theory was introduced [16]. To propose a dynamic non-zero-sum game model with concepts like relative advantage and advantage coefficient, solved using a multi-strategy fusion Particle Swarm Optimization (PSO) approach. Results confirm effectiveness via simulation. Limitations include reliance on simulation-based validation and possible challenges in real-time scalability. Modelling and evaluation methods for Cooperative Operation System-of-Systems (COSoS) involving manned aerial vehicles (MAVs) and UAVs were described [17]. To discuss standard framework-based and complex network-based modelling approaches, comparing their characteristics. Results summarize current effectiveness evaluation methods. Limitations include a lack of unified evaluation standards and challenges in real-world COSoS implementation. To improve UAV threat assessment in air defence using a dynamic fuzzy multi-attribute decision-making model [18]. To propose a 3D evaluation system—capability, opportunity, and intention combined with inverse Poisson-based time weighting and improved TOPSIS for threat prioritization. Results show enhanced accuracy and Limitations include complexity in real-time deployment and reliance on accurate intention estimation. Intrusion malware detection in UAVs by highlighting vulnerabilities in communication, software, and hardware systems are determined [19]. To present a taxonomy of detection methods using machine and deep learning algorithms, recent advances, and identify gaps. Results summarize current progress. Limitations include evolving threat complexity and limited real-time deployment evidence. Table 1 demonstrates the overall performance of previous work.

Table 1: Summary of the related work

References	Aim & Proposed Method	Results	Limitations
Mishra, and Palanisamy [10]	Improve multicopper reliability under counter-UAV threats via a modular autopilot system using a fuzzy inference-based controller with image recognition from six map sectors.	Enhanced autonomous navigation and trajectory tracking.	No practical deployment; limited real-world testing and adaptability.
Sarkar et al. [11]	Predict energy consumption in low-cost UAVs using AI models: Random Forest (RF), Regression Tree (RT), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Adaptive Neuro-Fuzzy Inference System (ANFIS) on a quadcopter flight dataset.	RF achieved the best prediction accuracy.	Weather impacts and UAV variations are not fully addressed.
Hu et al. [12]	Reduce computational demands in UAV swarms using fuzzy multi-agent reinforcement learning (FMARL), modelling interactions via fuzzy game theory.	Lowered storage and floating-point operations while maintaining effective control.	Potential loss of detail due to fuzzification/defuzzification.
Xia et al. [13]	Develop a hybrid control system combining Soft Actor-Critic (SAC) and Fuzzy Inference System (FIS) for real-time path planning.	Effective path planning and intruder tracking.	Simulation-based; lacks real-world validation.
Jasim et al. [14]	Evaluate UAVs in precision agriculture using Fuzzy-Weighted Zero-Inconsistency (FWZIC) and Fuzzy Decision by Opinion Score Method (FDOSM).	Payload emerged as the most critical criterion.	Based on expert opinions; context-specific criteria.
Shcherban and Eremenko [15]	Enhance autonomous power monitoring for UAVs using LPAB and fuzzy logic to estimate remaining flight time.	Improved energy use and safer UAV landings.	Relies on sensor accuracy and environmental factors.
Wu et al. [16]	Use game theory and a non-zero-sum model with relative advantage coefficients and PSO for UAV swarm decision-making.	Model validated via simulation, showing effective outcomes.	Limited to simulation; scalability concerns.

Wang et al. [17]	MAV/UAV COSoS modelling using standard frameworks and complex networks and evaluate effectiveness.	Summarized modelling and evaluation strategies.	No unified standards; real-world implementation difficulties.
Niu et al. [18]	Improve UAV threat assessment using fuzzy multi-attribute decision-making with dynamic variable weights and enhanced TOPSIS.	Better threat prioritization in dynamic environments.	Complex real-time deployment; depends on accurate intention inputs.
Cai et al. [19]	Intrusion malware detection in UAVs; present taxonomy using ML and DL algorithms.	Comprehensive overview of current approaches and progress.	Rapidly evolving threats; limited real-world system integration.

2.1 Research gap

The existing methods on UAV threat detection based on the literature exist with multiple critical limitations that highlight the potential use of MFIS in regard to adaptivity, decision rules, and computation load. For example, the fuzzification methods in FMARL lead to removal of granularity, and even after significant validation, can still not be practically deployed; Image-based fuzzy controllers continue to exist without validation for deployment; AI energy prediction methods for MCDM assessment models that did not address environmental influences; and UFMS models such as SAC-FIS rely heavily on simulation-based development that do not address real-world applicability. Furthermore, multi-criteria decision making based fuzzy frameworks continue to be driven by expert judgment, which provides a level of subjectivity at multiple levels of application in the estimation of weights in fuzzy reasoning, and malware detection general methods for UAVs show silent integrations with real-time systems. All these demonstrate poor flexibility, static decision rules and high computation loads. Therefore, the proposed methods of designing MFIS as fuzzy MCDM suspect with data normalization in real-time, principles of PCA derived feature reduction, and scalable fuzzy rule base, provide a pathway for adaptive, scaling, and valid classifications of a UAV's behaviour in real-time and in different dynamic FANET environments, coupled with potential threat mitigation.

3 Methodology

The methodology involves monitoring the UAV behavioural dataset for threat classification and detection and countermeasure deployment using fuzzy logic-based decision systems to enhance communication security in FANETs by identifying and mitigating potential threats. UAV behavioural data was utilized in this research and Min-max normalization and PCA were applied for preprocessing and feature selection. An MFIS computes a dynamic honesty score based on key parameters. The system classifies UAVs and recommends countermeasures, enhancing threat classification and detection, network reliability, and energy efficiency. Figure 2 shows the general flow of the fuzzy logic decision-making process, from data capture through threat assessment and final response selection.

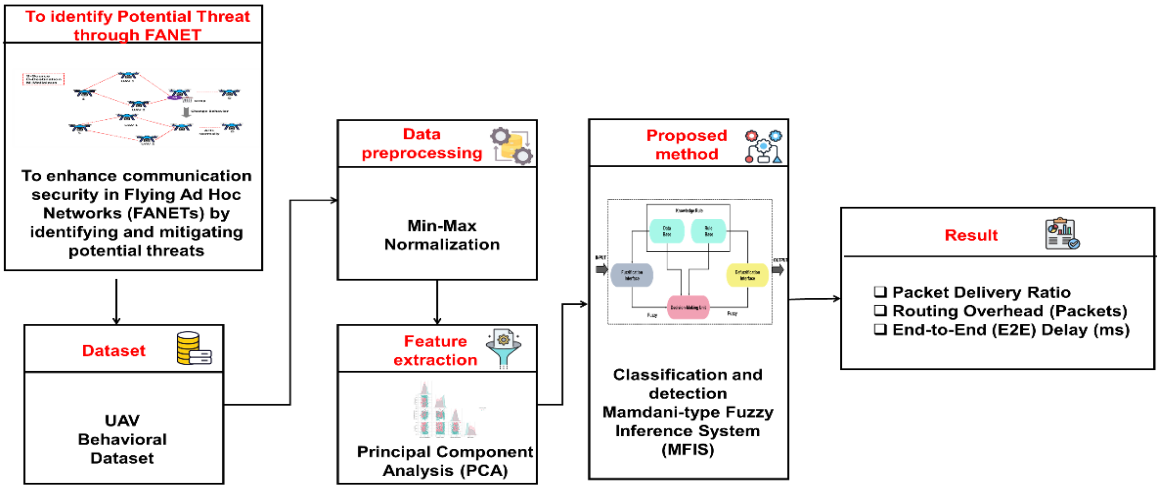


Figure 2: Overall flow of the proposed UAV countermeasure approach using fuzzy logic

3.1 FANETs

Using fuzzy logic for UAV countermeasures aims to reinforce communication safety in FANETs with accurate threat classification and detection and mitigation. The capacity of fuzzy logic systems to accommodate uncertain and vague data makes them suitable solutions for mobile environments such as FANETs that are characterized by

signal hops and unpredictable threats. Through monitoring key indicators, the fuzzy logic methodology can identify anomalies or threats to network security. For the security of communication in the network, it engages in such acts as the encryption of signals, isolation of drone, or modification of routing. Fuzzy logic increases communication assurance in FANETs by managing uncertainty in data and security by assessing signal quality, drone behaviour, and traffic patterns to determine possible security threats. It allows for responsiveness such as encryption, blocking a drone's messages, deploying an alternative drone, and modifying routing, as identified in Figure 3.

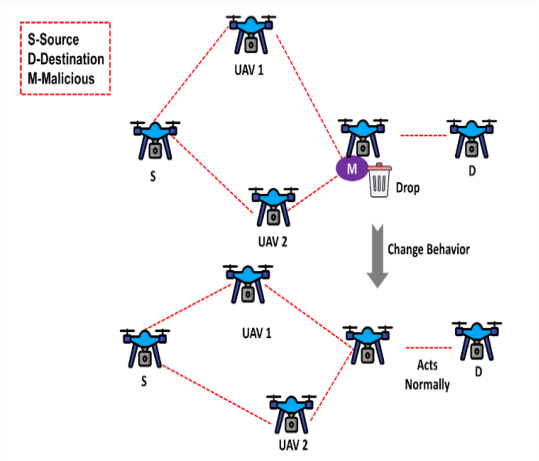


Figure 3: Resilient communication architecture in FANETs using Fuzzy Logic

3.2 Data collection

The data is a synthetic dataset with 1,000 instances to mimic the different behavioural characteristics of UAVs for use in research on fuzzy logic-based countermeasure systems, and intelligent threat classification and detection. Each instance can be characterized by four behavioural metrics: energy consumption, mobility pattern, packet transmission, and link stability. These metrics can be used to differentiate between cooperative UAV behaviour and malicious UAV behaviour.

The dataset can be used to develop intelligent decision-making models using labelled data with *behavior_label* indicating if the UAV behavior is cooperative (0), or malicious (1). The key features description is shown in Table 2.

Table 2: Feature description table

Feature Name	Description	Data Type / Range
energy_consumption	Power usage of the UAV in joules	Continuous (Joules)
mobility_pattern	Normalized movement variability (0 = stable, 1 = erratic)	Float (0–1)
packet_transmission	Successful packet transmission percentage	Percentage (0–100%)
link_stability	Communication links quality and consistency	Float (0–1)
behavior_label	UAV classification: 0 = Cooperative, 1 = Malicious	Categorical (0 or 1)

Source:https://www.kaggle.com/datasets/ziya07/uav-behavioral-dataset/data

Data Exploration: The data exploration shows pairwise relationships between key features, such as energy consumption, mobility pattern, packet transmission, and link stability, for two UAV behaviour types (labels 0 and 1), likely representing normal and indirect patterns. Kernel density plots reveal distribution differences; evasive UAVs (label 1) exhibit lower link stability and higher energy consumption.

These patterns support fuzzy logic-based classification by highlighting feature separability, enabling adaptive countermeasures through decision rules. Figure 4 shows the data exploration outcomes and data exploration highlights behavioural differences between normal and evasive UAVs. Evasive patterns show higher energy consumption and lower link stability, supporting fuzzy logic classification by emphasizing feature separation for adaptive threat classification and detection and countermeasure selection.

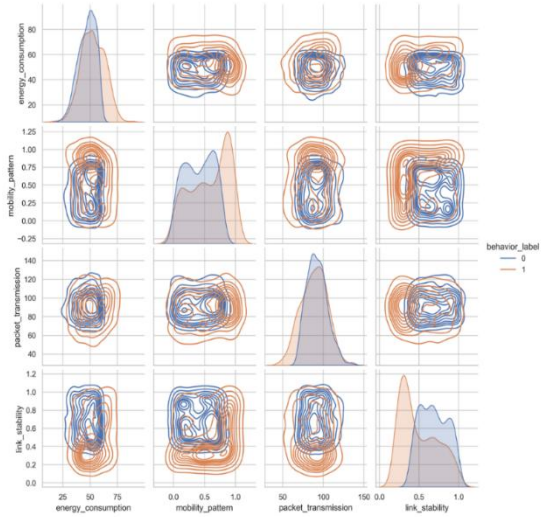


Figure 4: Feature distribution analysis for UAV behavioural classification

3.3 Data preprocessing

Data preprocessing for UAV countermeasures using fuzzy logic involves Min-Max normalization to scale sensor input data key parameters, between 0 and 1. Fuzzy logic is used in the research to enhance decision-making of aerial threats using UAVs through threat classification and detection, evasive manoeuvres, and adaptive control decisions.

Data preprocessing techniques to prepare sensor inputs to the fuzzy inference system are paramount in this process. The Min-Max normalization technique is applied to scale important UAV sensor characteristics, e.g., speed, altitude, and threat proximity, to a common range of [0,1]. This transformation improves the consistency of input values, allows for better computational efficiency, and improves understandability and responsiveness for the fuzzy logic system. as obtained in Equation (1).

$$X_{new} = \frac{X - \min(W)}{\max(X) - \min(X)} \quad (1)$$

W_{new}- The adjusted value derived from the normalized outcomes

W- Old value

$\max(x)$- The dataset's maximum value

$min(x)$- The dataset's minimum value

This preprocessing step guarantees a balanced assessment across data input variables while mitigating any bias from differential scales. By creating better consistency of data ranges, the system is better poised to accurately evaluate threats, and to adaptively respond to them in real-time in FANET scenarios.

3.4 Feature extraction using PCA

Feature extraction using PCA in UAV countermeasures based on fuzzy logic involves reducing the dimensionality of sensor data while preserving essential features. The efficiency and effectiveness of UAV countermeasure systems by integrating fuzzy logic and dimensionality reduction techniques that correctly identify and factor in the most important behavioural dimensions. PCA supports this through feature extraction as plan to minimize the dimensionality of UAV sensors and target data while still retaining critical features needed for quick classification and detection of threats, fast navigation, and making evasive decisions. PCA takes a set of variables that may be correlated and transforms them into a smaller number of uncorrelated variables called principal components, ordered by the amount of variance it explains from the original data. PCA allows the fuzzy inference system to reduce the input space, which benefits computational performance and understanding of the system. Assuming that $w_1, w_2, \ldots\ldots, w_l \in \Re^m$, security issues around energy data management are taken into consideration during PCA computation.

Determine the mean vector μ in m-dimensions by Equation (2).

$$\mu = \frac{1}{l}\sum_{j=1}^{l} w_j \quad (2)$$

The mean of all input vectors is computed across each dimension to center the data. This equation calculates the overall average (mean) across all UAV sensor observations for each dimension (speed, altitude, threat offset, etc.). Centring the data by simply subtracting this average ensures that PCA will ultimately detect not the absolute location of the UAV in feature space, but the variability of the UAV behaviour in feature space. This makes the fuzzy system more responsive to the real behaviour patterns in the data, as opposed to noise.

$$T = \frac{1}{l}\sum_{j=1}^{l}(w_j - \mu)(w_j - \mu)^s \quad (3)$$

Determine the observed data's estimated matrix of covariance T by Equation (3). $(w_j - \mu)^s$ is the transpose of the centered vector. This equation quantifies how much each pair of sensor features covaries across all UAV observations. When fully understood, these relationships are leveraged through PCA to determine what combinations of features are most salient for differentiating normal UAV behaviour from threatening ones. This improves the quality of input into the fuzzy system to facilitate better decision-making in response to threats. Determine the associated eigenvectors and eigenvalues of T, whereby $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_l \geq 0$. Determine the primary components from the l original variables by Equation (4).

$$z_1 = b_{11}w_1 + b_{12}w_2 + \cdots + b_{1l}w_l$$
$$z_2 = b_{21}w_1 + b_{22}w_2 + \cdots + b_{2l}w_l \quad (4)$$
$$\cdots$$
$$z_l = b_{l1}w_1 + b_{l2}w_2 + \cdots + b_{ll}w_l$$

These equations convert the initial sensor data into new, uncorrelated features (principal components) that better capture the variation present in UAV behaviour. These features reduce redundancy and improve the clarity of the fuzzy logic system inputs thus directing its attention towards truly meaningful patterns in the data that can be used for the classification and detection and control of threat responses. It is orthogonal that z_l are uncorrelated. As much of the initial variation in the data set can be explained by z_1, as much of the residual variance can be explained by z_2, etc. In the most useful data sets, a small number of bigger eigenvalues often outnumber the others, as follows in Equation (5). b_{11} describes the coefficients (elements of eigenvectors) used for projecting original vectors into the new space. These components z_l are orthogonal and uncorrelated, forming a new feature basis. Where the proportion maintained in the data format is denoted by z_l. PCA was used for feature extraction with the requirement to retain the extracted main components that explain at least 80% of the total variation. Figure 5 presents the feature importance of the dataset.

$$\gamma_l = \frac{\lambda_1+\lambda_2+\cdots+\lambda_n}{\lambda_1+\lambda_2+\cdots+\lambda_n+\cdots+\lambda_l} \geq 80\% \quad (5)$$

γ_l is defined as the total variance captured by the first n components. It ensures that the reduced space still reflects the majority of the original data information content. Utilizing PCA in this approach allows the UAV countermeasure system to only process the more relevant features of behaviour, allowing the computational load to be dramatically reduced and increasing the overall decision accuracy) of the system. Moreover, privacy limitations have been addressed by removing class labels from the behavioural features presented; the UAV countermeasure system is therefore solely focusing on the de-identified numerical data and statistical features of behaviour, specifically in energy-sensitive applications. This equation guarantees that the chosen principal components retain at least 80% of the original data's total variance. It ensures that most of the useful information about UAV behaviour is preserved after the dimensionality reduction; therefore, the fuzzy system can work properly without sacrificing accuracy. The pair plot visualizes feature distributions and relationships between UAV behaviours (label 0 = cooperative, 1 = malicious). Malicious UAVs tend to show higher energy consumption, erratic mobility, lower packet transmission, and reduced link stability, enabling fuzzy logic to distinguish patterns and support adaptive threat classification and detection shown in Figure 5. To conduct 20 experimental runs to capture performance variability.

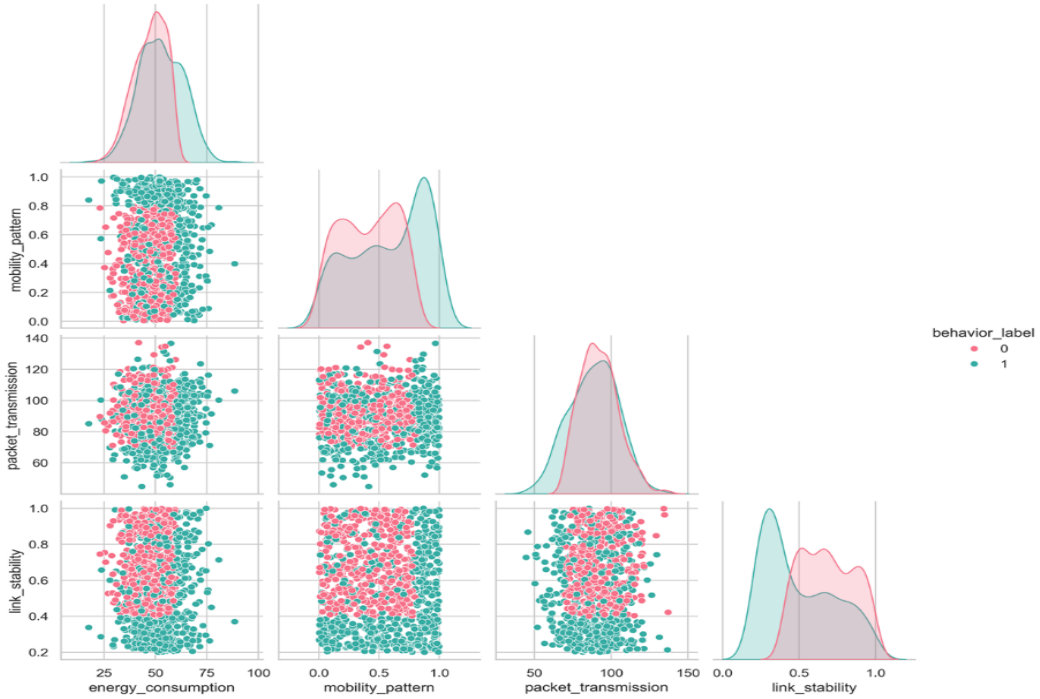


Figure 5: Feature Importance of the proposed dataset

The Table 3 summarizes the percentages of variance explained by the principal components. The first component accounts for 52%, the second accounts for 22%, and third component accounts for 11% and the last

four components together account for 15%. This indicates that there is some concentration in the distribution of variance.

Table 3: The distribution of variance

Component	Variance Explained (%)
1	52
2	22
3	11
Others	15

To settled on 3 retained components, totaling 85% of the variance (Component 1 = 52% (12826/31940), Component 2 = 22% (7081/31940), Component 3 = 11% (3582/31940)). This is consistent with the generally accepted 80% threshold for cumulative variance retention, which is commonly noted in UAV threat classification and detection studies. A scree plot of the eigenvalues used, is provided in Figure 6.

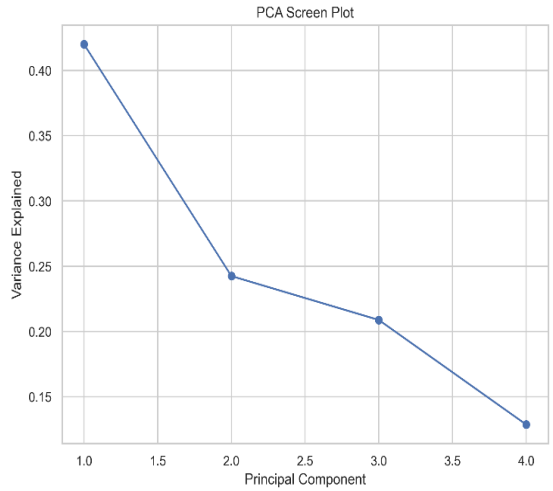


Figure 6: Scatter plot for PCA

3.5 Classification and detection using mamdani-type fuzzy inference system (MFIS)

An MFIS is employed in UAV countermeasures to classify drones as cooperative or malicious based on behavioural inputs. The system uses a rule-based approach with fuzzy logic to handle uncertainty and imprecision, evaluating input variables through membership functions and inference rules. By translating ambiguous behaviour into actionable classifications, MFIS enhances threat classification and detection, supporting real-time decision-making in autonomous aerial defence systems against potential malicious UAVs. The proposed MFIS employs triangular and trapezoidal membership functions for fuzzification, followed by minimum (min) T-norm for handling logical AND operations during rule evaluation, and maximum (max) S-norm for aggregating outputs from multiple rules. Finally, the Mean of Maximum (MoM) method is used in the defuzzification phase to obtain a crisp control output from the fuzzy set. To elaborate on the fuzzy logic system components. The MFIS employs triangular and trapezoidal membership functions for the four input variables—energy consumption, mobility pattern, packet transmission, and link stability—each with three linguistic terms (low, medium, high). These combinations form a total of 45 fuzzy rules, which are expert-defined to capture UAV behaviour patterns.

➢ ***Fuzzification using a knowledge rule***

Using the normalized scale $[0,1]$, it identifies data and rules based on the values of the observations $w, z, x, ..$, for the value of w determined at the time s, also defines $w(s) \in [0,1]$. Each of these observables $(w, z, x, ..)$ corresponds to a limited number of atomic sentences, as shown in Equation (6).

$$W_1, W_2, .., Z_1, Z_2, .., X_1, X_2 \ldots. \quad (6)$$

W_j is the linguistic term for input variables w (eg., high deviation), Z_j is the linguistic term for input variables z (eg., Medium delay), X_j is the linguistic term for input variables x (eg., High threat), These are atomic sentences that represent the linguistic terms (e.g. "High altitudes", "Low battery") corresponding to the input and output variables of fuzzy logic thermal context. The atomic sentences define the vocabulary in which fuzzy rules can be expressed such as "IF flight deviation is high THEN threat level is high, which connects to the purpose of assessing UAVs' ambiguous behaviours. Defines the linguistic variables (e.g. "high speed", "low energy") that characterize input and output behaviours.

The union of the atomic phrases thus forms the language V that is linked to the system. It considers the $FORM_V$ over the V set of formulas. It refers to a function e: $[0,1] \rightarrow [0,1]$ as a fuzzy set concerning observations. The selection of an infinite number of sets of fuzzy values over each observable is known as fuzzification of the observations w, z, x,..., and results in functions, as follows in Equation (7).

$$e_1, e_2, .., h_1, h_2, .., g_1, g_2 \ldots \quad (7)$$

e_1 membership function for W_j, applied to input w, h_1 membership function for Z_j, applied to input z, g_1 membership function for x_j, defining fuzzy output values. These functions assign degrees of truth for the atomic sentences, where inputs (for example, deviation, delay) are mapped and assigned to values between 0 and 1. These

fuzzy sets allow the system to classify UAV behaviours "softly," thereby acknowledging the uncertainty that is important for detecting potential threats in real time. Defines fuzzy membership functions to evaluate the degree of truth of every linguistic term.

The function of e_1, for example, in logic, is to give the associated atomic sentence W_1 a way to be assigned a level of truth. Specifically, at the time s, w is $w(s) \in [0,1]$. Then $e_1(w(s))$ is the level of truth of W_1. Immediately, it follows that the fuzzification of the observations w, z, z,... uniquely determines an atomic assignment at each instant s, as obtained in Equation (8).

$$\bar{\mu}_s(W_j) = e_j(w(s)), \bar{\mu}_s(Z_j) = h_j(z(s)), \ldots \quad (8)$$

$w(s)$ and $z(s)$ are the real-time input values at time s, $\bar{\mu}_s(W_j)$ is degrees to which $w(s)$ satisfies fuzzy set W_j, and $\bar{\mu}_s(Z_j)$ is described as degrees to which $z(s)$ satisfies fuzzy set Z_j. Assign a truth value for each observation (e.g. how true is "speed is high" at time ss) using the corresponding fuzzy membership function. This creates the fuzzy input vector at any given time step, allowing raw UAV behaviour to be transformed into a fuzzy logic-capable format. Evaluate the truth value of each atomic sentence at time s using membership functions.

It is particularly, to choose a model; the system is irrelevant. It fixes a many-valued logic $\mathcal{L}$ by selecting a t-norm *: [0, 1]2 → [0, 1]. The atomic assignment then uniquely extends to an assignment since $\mathcal{L}$is is truth-functional, as shown in Equation (9).

$$\mu_s: FORM_V \rightarrow [0,1] \quad (9)$$

Given the logic $\mathcal{L}$ and the fuzzification applied to fuzzy logic, each formula $\phi \in FORM_V$ of $\mathcal{L}$ might be provided with a distinct truth value at each instant s. Extends the atomic truth assignments to whole fuzzy logic rules using many-valued logic (with some t-norm operation such as MIN). This allows logical reasoning about fuzzy rules, which is the fundamental mechanism for discerning whether a UAV is malicious or safe. Extends atomic assignments (from Eq. 8) to whole fuzzy logic rules using many-valued logic.

➢ ***FIS***

The fuzzy inference, specifically fuzzy control systems. The Mamdani-type inference follows in logical recasting. Instead, it will strive to be in line with accepted practices. It may be interpreted as Mamdani-type reasoning. Fuzzy inference may be summed up as follows.

Phase 1: The observables $w, z, x, .,$ should be divided into two non-empty, disjoint subsets: the input observables $\{w, z \ldots\}$ and the output observables $\{x, \ldots\}$. Should the language V be divided into the following sets: input variables $\{W_1, W_2, \ldots, Z_1, Z_2, \ldots\}$ and output variables $\{X_1, X_2, \ldots,\}$ Additionally, divide the fuzzy sets into the following collections: input fuzzy sets $\{e_1, e_2, \ldots, h_1, h_2, \ldots\}$ and output fuzzy sets $\{g_1, g_2, ..\}$.

Phase 2: Establish a limited set of rules of the following type: X is (NOT) W_j if w is (NOT) W_j AND z is (NOT) Z_i THEN x is NOT X_i... It maintains that W_j is negated when the NOT is contained in "w is (NOT) W_j," and the same is true for $Z_i, X_l, ..,$

Phase 3: For each rule Q as in (M2), given the resulting input values $w(z), z(s), \ldots$ at time s, set, as follows in Equation (10).

$$Q_s = \min\left\{e_j'(w(s))\right), h_i'\left(z(s)\right), \ldots,\} \in [0,1] \text{ were,}$$
$$e_j'(\dot{w}(s)) =$$
$$\begin{cases} 1 - e_j(w(s)) if\ W_j is\ negated\ in\ Q \\ e_j(w(s))\ Otherwise \end{cases} \quad (10)$$

Calculates the firing strength of a fuzzy rule at time ss using the minimum T-norm for logical ANDs. When computing firing strength, to determine the impact of UAV behaviour on rules. As an example, if a UAV has a high deviation behaviour and has bad communication, the corresponding rule for "malicious UAV" would fire strongly. Computes the firing strength of a rule at time ss, using MIN t-norm for logical AND.

Phase 4: Using the function Q_s, create the resulting fuzzy set of rule Q, at the time s for each Q_s calculated in phase 3: Given by $g_l^s: [0,1] \rightarrow$, as follows in Equation (11).

$$e_j'(\omega) = \begin{cases} \min\{Q_s, 1 - g_l^s(\omega)\}\ if\ X_l\ is\ negated\ in\ Q; \\ \min\{Q_{s,} g_l^s(\omega)\}\ Otherwsie \end{cases} \quad (11)$$

Produces a fuzzy output set given the input firing strength $Q_{s,}$ and the output fuzzy set g_l^s of the rule. Creates the output response (e.g., a threat level), still not crisp, but fuzzy indicating something along the lines of "likely malicious". Creates the fuzzy output set from a rule, and modifies it for output negation.

Phase 5: The function $E_s: [0,1] \rightarrow [0,1]$ is defined as the aggregate output fuzzy set at time $s$in Equation (12).

$$E_s = \max\{g_l^s\} \quad (12)$$

E_s is described as the agreed fuzzy output at time s for output value (w), max is the logical OR to combine multiple rule consequences. It takes all individual rule outputs and combines them into a single fuzzy output set using the maximum (S-norm) operation. This considers the collective decision of the system at time ss based on all individual rules and provides a joint fuzzy evaluation of the UAV behaviour.

It takes all rule outputs and combines them into a single fuzzy output set using the MAX S-norm.

Consequently, as in phase 4, the maximum of all rules ranges throughout the output fuzzy sets. Consequently, Mamdani-type inference yields the fuzzy set E_s at each instant s, as shown in (phase 5).

➢ ***Defuzzification***

The fuzzy set E_s: $[0,1] \rightarrow [0,1]$ is the result of a Mamdani-type inference at time s. The range of normalized values for the physical observation x that has to be controlled is known as the domain of E_s. To have real control, x needs to be set to a certain value $\omega_s \in [0,1]$. This is accomplished by defuzzifying E_s.

It assumes decision support that the well-known mean of the maximum defuzzification method is used to calculate ω_s from E_s. It shows how ω_s is calculated when utilizing discrete approximations to E_s. Assume the set of sample points $T = \left\{\frac{1}{m}\middle| m = 0,1,\ldots,M\right\} \subseteq [0,1]$ after selecting an integer $M > 1$. Set $N_s = \{t \in T | E_s(s) = \max_{w \epsilon T} E_s(\omega)\}$ to extract those that maximize E_s over T, as obtained in Equation (13). Figure 6 presents the MFIS structure.

$$\omega_s = \frac{\sum_{t \in N_s} T}{|N_s|} \quad (13)$$

Converts the fuzzy output $E_s(s)$ into a crisp control value $\omega_s \in [0,1]$ $omega_s$ in [0,1] by averaging the values where $E_s(s)$is highest. This crisp output is essential for taking decisive control actions like activating countermeasures or issuing alerts perfectly aligning with the objective of actionable, real-time UAV threat classification. The proposed MFIS uses fuzzy logic to classify UAVs as cooperative or malicious by evaluating behavioural inputs. It applies fuzzy rules, membership functions, and defuzzification to support real-time decision-making for adaptive UAV countermeasures in uncertain environments as shown in Figure 7.

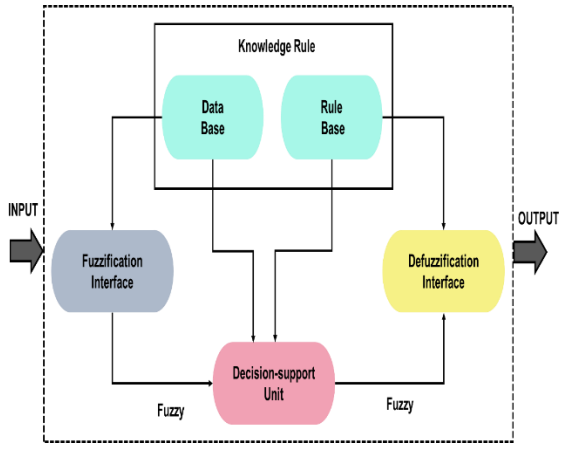


Figure 7: Architecture of the Proposed MFIS for UAV threat classification

4 Result

This section deliberates on the results produced by the implementation of the model, including parameter setup, evaluation criteria, and comparative phase.

4.1 Experimental setup

Python 3.8 made multitasking and development duties demanding performance evaluations much easier due to this modern laptop design as shown in Table 4.

Table 4: Experimental setup

Aspect	Details
Hardware	Intel Core i7 CPU, 16 GB RAM, NVIDIA GTX 1660 GPU
Software Stack	Python 3.8, scikit-fuzzy, NumPy, Pandas
Training-Validation Split	80% training, 20% validation

4.2 Hyperparameters

MFIS parameters as described in Table 5.

Table 5: Parameter's setup

Parameter	Value/Setting
Number of Input Variables	4 (Energy, Mobility, Transmission, Link Stability)
Membership Function Type	Triangular, Trapezoidal
Number of Membership Functions	3 (Low, Medium, High)
Rule Base Size	45 rules
Inference Method	Mamdani-type inference
Fuzzy T-norm Operator	Minimum (min)
Fuzzy S-norm Operator	Maximum (max)
Defuzzification Method	Mean of Maximum (MoM)
Normalization Technique	Min-Max Normalization
Number of Principal Components	3 components
Variance Retained (PCA)	≥ 80%

4.3 Evaluation criteria

The proposed MFIS approach showed good performances on all evaluation metrics. The ROC and PR curve evaluations have provided evidence of accurate threat classification and detection, and the energy & mobility pattern analysis has demonstrated the energy-efficient UAV countermeasures.

4.3.1 ROC Curve

The performance of a fuzzy logic-based UAV countermeasure system was evaluated. The curve shows a high true positive rate across almost all false positive rates, indicating strong classification performance. The AUC is 0.98, suggesting the model is highly effective at distinguishing threats from non-threats in fuzzification strategy for mitigating fuzzy logic. The steep rise near the y-axis reflects excellent sensitivity with minimal false alarms, making the system suitable for real-time UAV threat classification and detection and response. Figure 8 demonstrates the impressive classification performance of the fuzzy logic-based UAV countermeasure system by having very high sensitivity with low false alarm rates, making it suitable for real-time threat identification and response.

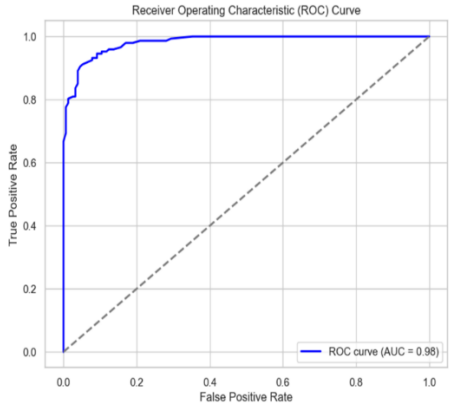


Figure 8: ROC Curve illustrating classification performance of the proposed MFIS-Based UAV countermeasure system

4.3.2 Precision-Recall (PR) curve

The PR curve evaluates the performance of a fuzzy logic-based UAV countermeasure model. The high area under the curve (AUC = 0.98) indicates outstanding classification performance which sustained high precision despite increased recall. It suggests that the model effectively detects threats (true positives) with minimal false alarms, making it highly suitable for real-time UAV threat mitigation. Figure 9 displays the PR curve outcomes.

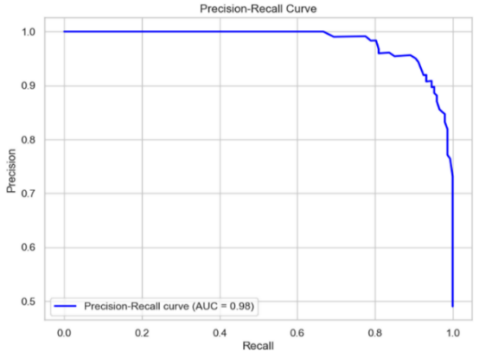


Figure 9: High-performance classification and detection accuracy is shown by the PR Curve for MFIS

4.3.3 Energy consumption vs mobility pattern

The relationship between energy consumption and mobility patterns in UAVs, segmented by behavior labels (0 and 1), is analyzed. The x-axis represents energy consumption, while the y-axis indicates normalized mobility patterns.

Two distinct clusters emerge: behaviour label 0 (in blue) generally reflects lower to moderate energy consumption and varied mobility, whereas behaviour label 1 shows broader energy usage and more consistent high mobility. In the context of UAV countermeasures based on fuzzy logic, this visualization helps identify behaviour patterns that can trigger adaptive responses for efficient energy management and mobility control under uncertain operational conditions. Figure 10 presents the outcomes of mobility pattern vs energy consumption.

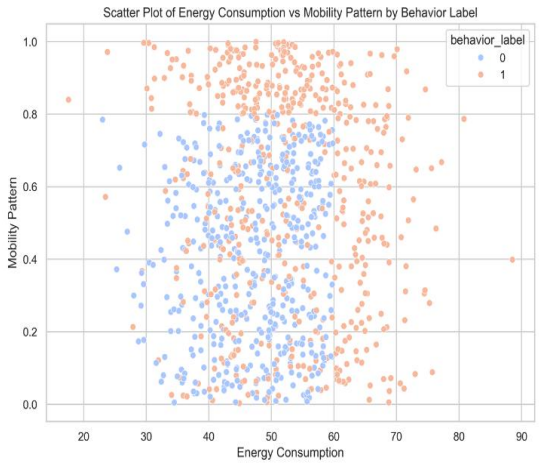


Figure 10: Energy consumption and mobility pattern using the proposed MFIS Method

4.4 Comparison phase

Python 3.12 made multitasking and development duties demanding performance evaluations much easier due to this modern laptop design. The result comparison parameters, such as packet delivery ratio, routing overhead, and end-to-end delay, are used to demonstrate the comparison of the proposed model, MFIS, with the traditional model, efficient honesty-based classification and detection scheme (EH-DS) [20].

4.4.1 Packet delivery ratio

The packet delivery ratio for the proposed MFIS method was compared with the existing EH-DS approach, showing significant improvement as the number of drones increases. The MFIS method consistently shows higher packet delivery ratio values across all drone counts compared to EH-DS. While EH-DS increases steadily, MFIS achieve significantly better performance, indicating more reliable and efficient data delivery. Figure 11 display the packet delivery ratio outcomes.

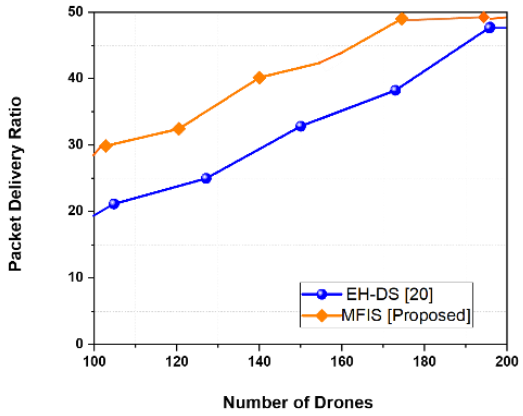


Figure 11: Comparison of packet delivery ratio

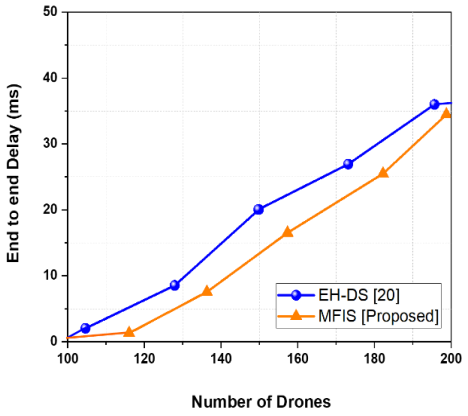


Figure 13: Result of the E2E delay

4.4.2 Routing overhead (packets)

The additional communication and processing burden placed on a network because of the transfer or routing of control or routing packets. MFIS demonstrates lower routing overhead throughout the range, with values remaining minimal even as the number of drone increases. In contrast, EH-DS shows relatively higher overhead, suggesting more control traffic and less efficient routing management. Figure 12 depict energy consumption with the growing number of drones.

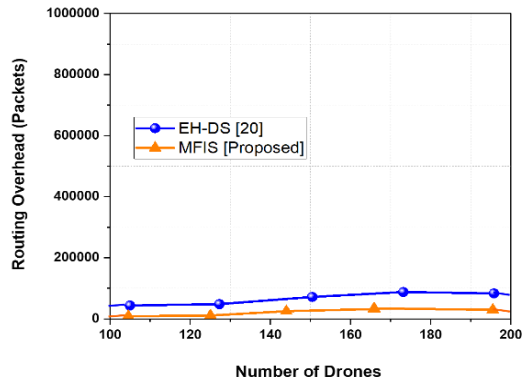


Figure 12: Representation of routing Overhead (Packets)

4.4.3 End-to-End (E2E) Delay (ms)

The E2E delay for UAV systems with different numbers of drones is compared, evaluating the proposed MFIS method with the existing method, EH-DS. The end-to-end delay for MFIS remains lower across all drone densities compared to EH-DS. As the number of drones increases, EH-DS experiences higher delays, whereas MFIS maintains better responsiveness and faster communication flow. Figure 13 demonstrate MFIS's superior scalability and efficiency in reducing communication latency, making it a more effective solution for real-time UAV operations under increased network loads.

4.5 Discussion

The research is primarily aimed at producing an intelligent fuzzy logic-based UAV countermeasure system (MFIS) that improves accuracy, energy efficiency, and communication reliability in constantly changing and different environments. EH-DS method [20], while functional, is limited in significant areas: static thresholds, low adaptability to noise, difficulty dealing with cooperative or spoofing attacks, and inattention to dealing properly with situations of very fast drone movements or complicated environments. Alternatively, the proposed MFIS method performs real-time fuzzification to obtain effectively adaptive decision-making mechanisms, resulting in improved packet delivery ratio and reduced time taken in acquisitions. Consequently, these advancements demonstrate that MFIS has superior performance across important metrics, and more importantly, better scalability and operational efficiency with increasing sizes of UAV networks. The proposed MFIS has many potentials to adapt fuzzy logic limits by providing real-time input normalization and dynamic rule evaluation to generate context-aware decisions. Conventional fuzzy logic systems tend to use non-adaptive sets of rules, but MFIS employs PCA-optimized feature refinement and use of input variability to contextualize retrospectively to improve the adaptation of UAVs to perceptions. In part, this will relax their reliance on fixed thresholds and their adaptability when dealing with UAVs as unique environmental system factors.

5 Conclusion

This decision-support approach for UAV threat identification and mitigation, based on fuzzy logic, uses a well-developed dataset that collects UAV behavioural information, including key parameters. Preprocessing strategies, including min-max normalization, ensure uniform data and reduce the effects of scaling issues, which strengthens the eventual analysis. Using PCA in feature extraction, critical attributes relevant to UAV

behaviour were emphasized. The system is designed to increase the safety of the messages in FANETs by detecting threats and countermeasures. The MFIS was used as the main tool, constantly computing a dynamic honesty score based on the features it received. This enabled dynamic labelling of UAVs as cooperative or malicious to facilitate the effective implementation of countermeasures. The simulation results show a significant improvement in performance parameters, including to-end delay, routing overhead (packets), and packet delivery ratio, by 15-55% compared to previous methodologies. The findings confirm the merits of the system to generate reliable and timely threat analysis and relevant advice without compromising operational effectiveness. Real-time processing speed and scalability remain a challenge, especially in cases of large networks of UAVs. The future improvements will focus on speed optimization and hybridization of the most modern hybrid methods, suitable for larger-scale usage. In future research, integrate realistic UAV mobility models such as Gauss-Markov or Random Waypoint (RWP) to simulate dynamic flight behaviours over time. It will apply statistical significance tests to compare MFIS and EH-DS, ensuring reliable performance validation across all metrics. It will address this by incorporating time-based UAV mobility datasets and real-time testing environments to comprehensively evaluate latency and computational overhead. It plans to enhance the system by integrating hybrid fuzzy systems, specifically a neuro-fuzzy inference mechanism, to allow adaptive tuning of membership functions and rule bases through learning. It also aims to incorporate reinforcement learning techniques to enable online rule adjustment based on real-time UAV behavioural feedback, allowing the system to continuously evolve and improve its threat classification and detection and response strategies. To incorporate statistical significance testing such as t-tests or ANOVA to validate performance gains by computing confidence intervals and p-values for reported metrics. Future work will incorporate statistical measures for both methods to strengthen performance comparison

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STFT-ENGB: A Hybrid Time Frequency and Gradient Boosting Approach for Power Quality Disturbance Detection

Guanghua Yang[1*], Rui Li, Xiangyu Lu, Yuexiao Liu, Na Li
State Grid Beijing Electric Power Company, Beijing, 100032
E-mail : ygh0718@163.com
*Corresponding author

Keywords: power signal processing, power quality disturbances (PQDs), smart grid, signal-piloted, short-time Fourier transform fused efficient natural gradient boosting (STFT-ENGB)

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Power signal processing is a specialized domain within signal processing that focuses on the analysis, interpretation, and manipulation of signals in electrical power systems. In modern smart grids, Power Quality Disturbances (PQDs) can result in considerable operational disruptions and financial losses for energy stakeholders. This research introduces a Short-Time Fourier Transform fused Efficient Natural Gradient Boosting (STFT-ENGB) model for robust recognition of power quality disturbances with energy grid applications. A comprehensive framework used for PQD identification by leveraging advanced power signal processing techniques and time-frequency-based feature extraction. The system collects electrical measurements from the power system includes voltage and current. The Z-score normalization is a preprocessing technique for reducing noise. The STFT is utilized to extract discriminative, time-localized features from the power signals. These extracted features are then combined using a late fusion strategy to form a unified representation. The proposed method was implemented using Python 3.10.1. Extensive experiments demonstrate that the proposed STFT-ENGB approach performs better than multimodal baseline architectures, achieving superior results, with accuracy, F1-score, recall, and precision ranging from 95% to 99%. These findings offer a promising solution for real-time power signal monitoring in smart grid environments, facilitating intelligent fault diagnosis and improving the overall resilience and responsiveness of modern electrical infrastructure.

Povzetek: Predstavljen je hibridni model STFT-ENGB, ki združuje časovno-frekvenčno analizo in izboljšano gradientno pospeševanje za zaznavanje motenj kakovosti električne energije. Z normalizacijo, STFT-izločanjem značilk in pozno fuzijo doseže dorbo napovedljivost ter omogoča zanesljivo diagnostiko v pametnih omrežjih.

1 Introduction

Power signal processing is a crucial field in electrical engineering that is important for many applications, including effective energy management, defect detection in electrical grids, and power quality assessment [1]. The complexity of electrical infrastructure has raised the need for high-performance algorithms for power signal evaluation. Such systems require precise, accurate, efficient power signal processing systems to both enhance system reliability and enhance anomaly detection [2]. Time-frequency analysis (TFA) has proved to be an effective technique for signal representation and feature extraction, since the conventional signal processing techniques did not consider the non-stationary nature of power signals. TFA is an integrated method of analyzing non-stationary power signals that fluctuate over time, combining frequency-domain and time-domain analyses [3]. Conventional methods tend not to be able for extract useful information from non-stationary signals, particularly in power systems where the signal suffers from noise, transients, harmonics, and the occurrence of other abnormalities [4]. These methods have improved feature recognition and system malfunction detection of power data, particularly significant for system performance and operational security. Most typical power signal features include noise, transients, and harmonics that can indicate some form of overall system malfunction due to faulty equipment or power quality issues [5]. Using the features present in power signals, it becomes possible to digitalize monitoring, fault detection and diagnosis, preventive maintenance, and system operation assessment. By extracting features from power data efficiently, the system has tremendous potential to realize the efficiencies available for quickly identifying potential systematic issues before they develop into issues of greater consequence [6]. More specifically, TFA techniques can enable more accurate identification of harmonic

distortion, frequency variations, and abrupt voltage transitions acquired from measurements. These techniques can also potentially provide more substantial diagnoses, improving the power system performance and reliability [7]. Power signal processing can greatly improve electrical grid and microgrid monitoring and control, particularly as the electrical grids become more renewable energy - Smart grids. The systems can provide more fault location, energy management, and predictive maintenance strategies to enhance both reliability and performance in the case of comprehensive feature identification [8, 9]. This research aims to create a new power signal processing method for TFA that successfully extracts features. By addressing the challenges of dynamic and non-stationary power signals, the method should achieve high accuracy for detecting abnormalities, transient phenomena, and failures in systems. [10]. The difficulty is to find a compromise between time resolution and frequency resolution, a common drawback of TFA methods. Finding balance depends on the preservation of algorithm performance in power system applications [11].
The formal research question was stated as follows;
How does the incorporation of the ENGB model increase the classification accuracy and computational lightness of PQD classification by conventional classifiers?
In What ways the STFT used for feature extraction to discriminate among different types of power quality disturbances in three-phase electrical systems?
How suitable the PQD detection model used to generalize various datasets and industrial conditions for different operating conditions and noise rates?
The objective of this research is to create a revolutionary Short-Time Fourier Transform fused Efficient Natural Gradient Boosting (STFT-ENGB) approach to enhance power quality disturbances with energy grid applications. The suggested approach enhances the detection of PQDs in low SNR conditions using hybrid spectral and probabilistic modeling. The key contributions of this research as follows,
Dataset Collection: A three-phase power quality event dataset was collected from Kaggle, it contains synchronized voltage and current signals across multiple disturbance classes.
Data Pre-Processing and Feature Extraction: The time-frequency analysis, Z-score normalization techniques used as preprocessing stages to normalize the data, which makes it ideal for smart grid applications.
Optimized Classification Model: An STFT-ENGB model used for identifying PQDs in a robust manner that improves smart grid system reliability.
Real-Time Results: The simulation results evaluate the precision, accuracy, recall, and F1 score for optimizing the smart grid with less computation utility.
The research structure is outlined as follows: The literature review section analyzes to provide background for the inquiry. The materials and methods section describes the data collection and analysis. Summarizes the findings, emphasizing critical findings in this section, provides a complete interpretation of the data, the concludes with an overview of the research's ramifications and future directions.

2 Related work

The relevant literature explores AI-driven power quality disturbance detection systems, focusing on adaptive boosting models, and intelligent data acquisition to enhance real-time fault recognition, computational efficiency, feature discriminability, and overall grid reliability in smart energy environments.
The method for converting a microwave frequency measuring system for utilizing TF into a TFA [12]. It also has two TFA relationships: parallel stimulated Brillouin scattering (SBS) for microwave TFA, and time-division SBS for TFA with great specificity for periodic signals. Simulations show how the system can be reconfigured in multiple dimensions. Fault diagnostics in rolling bearings are critical for forecasting damage and minimizing financial losses [13]. A multi-rolling component fault identification approach integrates the time-frequency analysis and a vibration signal produced by multi-curve extraction techniques, thereby improving weak periodic fault impulses and finding homologous defects. The experiments conducted show that TF separation (TFS) and identification are effective. STFT-based approaches are inadequate for processing non-stationary signal data in fluctuating operational environments [14]. TFA technique enhances instantaneous frequency (IF) curves by increasing initial frequency and using a synchro squeezing operator, improving time-frequency accessibility and feature extraction capability. Table 1 presents a summary of related work on power quality disturbance detection.

Table 1: A summary of related work on the power quality disturbance detection

Ref	Technology Used	Objective	Result	Challenges
[15]	Time-Frequency Analysis (TFA)	To assess power quality affected by nonlinear loads due to power electronics-based renewables	Identified the need of TFA methods to analyze time-dependent waveforms	Time-varying voltage and current waveforms complicate reliable power quality assessment
[16]	Convolutional Neural Network (CNN)	To detect and monitor health conditions like epilepsy using EEG signals	Achieved high accuracy, precision, recall, and F1-score using 3570 EEG signal pairs	Effective integration of multiple TFA approaches in biomedical signal processing was a challenge
[17]	TF Self-Similarity Enhancement Network (TFSSEN): includes adaptive TF characterization, attention residual group, mixed-scale TFA	To identify mechanical issues in nonstationary signals from wind turbines	Improved detection accuracy for mechanical problems using enhanced TF features	Complexity in analyzing nonstationary signals and combining global/local attention mechanisms
[18]	Deep learning, transfer learning	To improve efficiency and accuracy in detecting and identifying bolt defects	Detection accuracy improved	Required algorithm optimization for better accuracy
[19]	LPSVM (Least Squares Support Vector Machine),	To reduce computational cost; and performance of SVM	Proposed model achieved 0.40 times the computational cost	Kernel complexity increases the computational load;
[20]	Interactive robot model, machine learning, signal processing, electric energy metering system	To enhance power quality monitoring and prediction under overload conditions	Achieved ideal prediction accuracy without sacrificing speed;	Conventional methods didn't meet accuracy expectations;

3 Problem statement

The challenge in several domains, including power systems and fault diagnosis is to process nonstationary signals, such as ECGs, vibration signals, and wind turbine signals more effectively, by using TFA techniques [13]. Most existing TFA works have some form of the limitations including noise sensitivity, low resolution, and impediments in process time-varying signals. More sophisticated techniques that can further facilitate signal reconstruction and accuracy for detection while leveraging even more advanced abilities for feature extraction are needed. TFA methods might not sensitive enough to measure quickly, and the nonlinear nature of waveforms caused by power electronics-based renewable sources [15]. These techniques were frequently sensitive or flexible and it was desirable to observe faint or temporary perturbations in different loading conditions. To overcome these limitations, the suggested STFT-ENGB approach, incorporate adaptive noise reduction techniques for improved input data quality, providing better performance robustness. The algorithm employs real-time feature extraction using STFT to minimize computational burdens and capture dynamic changes effectively. The flexibility in STFT-ENGB makes it possible to fine-tune and verify it for a variety of power systems and operating regimes.

3.1 Methodology

The previous section reviewed recent studies on power quality disturbance detection. These studies highlighted shortcomings in computational efficiency, real-time responsiveness, and adaptive data acquisition, and the proposed model explained the research gap to address these issues.

The approach combines several advanced signal processing methods for power quality event analysis. It applies Z-score normalization for data standardization, STFT for feature extraction, and ENGB for better feature extraction. The combined STFT-ENGB association improves the resilience and precision of power signal analysis, particularly in fault recognition and categorization. The hybrid approach maximizes signal processing by reducing and enhancing feature extraction. Figure 1 depicts the methodological flow for the system under consideration.

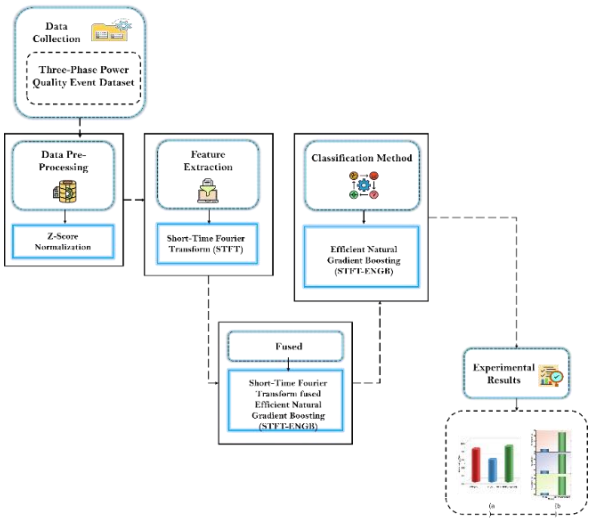


Figure 1: Flow of the recommended system for the proposed methodology

3.2 Data gathering

The power quality event dataset was gathered from the open-source Kaggle website https://www.kaggle.com/datasets/zoya77/three-phase-power-quality-event-dataset. The dataset provides electricity measurements from a three-phase power supply gathered throughout time. The dataset consists of 100 samples per class, total of about 600 recordings. Each signal has a 3-phase voltage and current waveform, with around 10 cycle's duration. It includes 6 event classes like voltage sag, swell, interruption, harmonics, flicker, and normal operation. The dataset was divided into training and testing samples, where the training samples have (70%) and the testing samples has (30%). Since the dataset was class-balanced with approximately 100 samples per class, no additional imbalance handling techniques like oversampling or class weighting were required. It was especially appropriate in the design and validation of classification models, fault detectors, and signal-processing algorithms in smart grids. The information contained in the dataset used to analyze the power distributions. The given dataset was capable to fully assist the purpose of creating a trustworthy real-time PQD detection system.

3.3 Data exploration

Figure 2 illustrates the feature importance analysis of power signal processing via TFA. The features, such as voltage and current phases of the three phases (A, B, C), are ordered according to the impact on the analysis. Voltage_phase_a, voltage_phase_b, and voltage_phase_c is of greater importance, indicating that the voltage signals of different phases play an important role in the analysis. The existing features, like current_phase_a, current_phase_b, and current_phase_c, possess relatively lesser importance. This emphasizes the significance of voltage signals in the time-frequency feature extraction process for STFT-ENGB.

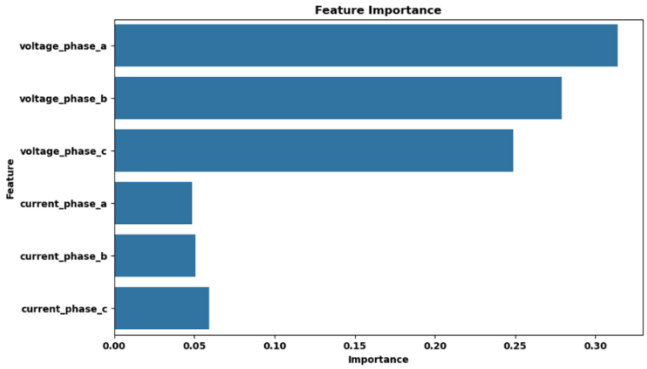


Figure 2: Feature Importance of power signal phases based on TFA

3.4 Z-score normalization using preprocessing technique

Normalization is essential when the preprocessing step, in particular while dealing with numerical characteristics in datasets linked to power signal processing and TFA. This method alters an intersection to maintain uniformity across changed features. Z-score standardization was used to normalize the various response variables, including power consumption signals and measurements of system performance. This method supports TFA-based anomaly detection, as it allows the information analyzed by the system to be altered from the original value to a normalized form such that the mean value is 0 and the standard deviation is 1. The formula for Z-score normalization is presented in Formula (1).

$$x' = \frac{x_j - G_j}{\text{std}(G)} \quad (1)$$

x^' = Normalization value results, x = The attribute's value that has to be normalized, G_j = The attribute's mean value, and std (G) = Attribute G for the standard deviation. Table 2 represents the output of Z-Score normalization.

Table 2: Output of Z-score normalization

voltage_phase_a	voltage_phase_b	voltage_phase_c	current_phase_a	current_phase_b	current_phase_c
-0.00	0.17	-0.15	0.06	1.15	-1.21
0.09	0.09	-0.16	0.79	0.50	-1.42
0.16	-0.02	-0.11	1.22	-0.20	-0.97
0.18	-0.15	-0.05	1.25	-1.08	-0.41
0.10	-0.18	0.10	0.80	-1.31	0.50
0.01	-0.17	0.18	-0.02	-1.08	1.16
-0.10	-0.05	0.16	-0.65	-0.57	1.44
-0.18	0.04	0.10	-1.36	0.39	1.08
-0.16	0.15	0.05	-1.35	0.95	0.28
-0.11	0.23	-0.09	-0.75	1.42	-0.60

3.5 Feature extraction using Short-Time Fourier Transform (STFT)

STFT provides a fixed time-frequency resolution which is predictable and simpler to be implemented in any practical setting of grid monitoring. Furthermore, a proper choice between the window functions and lengths, the consequences of spectral leakage in STFT. The SIFT was capable of uniformly sampling localized transient events with reduced processing requirements makes it an appealing option to the suggested power quality disturbance detection system. The STFT is an influential signal processing technique that partitions signals into short, overlapping segments and applies the STFT to each segment. This way it analyzes a signal's frequency and time characteristics, which is ideal for non-stationary signals by changing characteristics over time. An STFT produces a time-frequency image that presents the energy content in the signal as a function of time and frequency. STFTs are typically used in power signal processing to produce a time-frequency image that can be interpreted to identify certain characteristics by looking for patterns in the frequency domain. It is necessary for a wide range of functions, from fault detection to classification of signal classification. STFTs can be found in a multitude of applications, including speech processing, biomedical signal analysis, and industrial monitoring.

An STFT on discrete-time, periodic signals in power signal processing, which often does not get the expected result of frequency response due to spectral leakage. Spectral leakage occurs because the energy of the signal spreads out across the frequency spectrum. When a finite segment of a signal is analyzed using a Fourier transform, the boundaries create discontinuities, causing the energy of that signal segment to be spread in the frequency domain. A signal's periodic extension can be misleading to the discontinuities punctuating the period, causing errors in its frequency representation. Given the role of spectral leakage in extracting features and analyzing power signals, it's important to understand and manage the error source, especially when analyzing signals in the time-frequency domain.

The functions are vital in power signal processing for analyzing discrete-time signals and reducing spectral or frequency leaking that occurs because of signal discontinuities that ensue at the limitations of data segments. Most electrical component functions decay to zero at the edges, accordingly to these window functions' properties, overlapping power signals should be used to not interfering with the data loss that occurs. To calculate the STFT of a discrete-time signal w(m), a window function x(m) is applied to each segment, and its frequency content is analyzed between time intervals. The STFT Formula (2) is given by:

$$\text{STFT}(m, l) = \sum_{m=0}^{M-1} w(m)x(m - nG)d^{-i\frac{2\pi}{M}lm} \quad (2)$$

When m is the sample index, l the frequency index, M the window length, x(m) the power signal function, n the power signal location, and G the hop size between consecutive electrical component systems. This is required for accurate feature extraction and time-frequency analysis in power applications that use signal processing.

3.6 Late fusion strategy

Late fusion strategy describes the combining outputs process of high-level feature representations from multiple modalities, after each modality has been processed independently through extracted features. The modalities were independently classified by using this approach, which constitutes the characteristics of each modality. Every modality was classified separately when the attributes had been integrated. This method has the benefit that each modality might learn its features by using the classifier. Vectors were then fused to generate the multimodal representation on equation (3), which conveyed a weighted combination. Where, F represents the attention modules.

F=Fusion (A,V) (3)

3.7 Efficient natural gradient boosting (ENGB)

The ENGB classifier using the electrical component for TFA in power signal processing relies on accurate feature extraction from complicated information. The ENGB model was used to increase its flexibility of variables' time-frequency representation exemplified by STFT. In specific, the losses will be customized to deal more adequately with the issue of class imbalance, and mechanisms of weighting features were integrated to draw more weight on transient-sensitive features. The ENGB model's hyperparameters were tuned by STFT. The associated notions and computation of time-frequency distributions are highly complicated, posing obstacles for use in practical engineering applications. The enhanced approach to generating TFA features establishes a connection between conventional signal processing approaches and TFA, utilizing sophisticated mathematical approaches. A scoring function T(θ,z_j) is calculated using Shannon information from signal characteristics subscripts 〖 z〗 _j, followed by Formula (4).

$$T(\theta, z_j) = -logO_\theta(z_j) \quad (4)$$

When O_θ (z_j) is the probability value of z_j, and θ is the characteristic vector of the prediction distribution. Let -logO_θ (z_j) = e (θ) and accomplish a Taylor expansion on e (θ + c '). The third- and higher-level terms have been eliminated to simplify the calculation using Formula (5).

$$e(\theta + c') = f(\theta) + c'^S \frac{\partial e(\theta)}{\theta} + \frac{1}{2} c'^S \frac{\partial e(\theta)}{\theta} \left(\frac{\partial e(\theta)}{\theta}\right)^S c' \quad (5)$$

Where, e(θ) indicates the error function, and c' depicts the transpose vector; $\tilde{\nabla}$ it represents the ENGB. Convert the Euclidean space to a statistical manifold, and utilize Formula (6) to extract signal features:

$$C_{LK} = \int_{-\infty}^{+\infty} O_\theta(z_s) * (e(\theta + c') - e(\theta)c(z_s) = \int_{-\infty}^{+\infty} O_\theta (z_s) * \left(c'^S \frac{\partial e(\theta)}{\theta} + \frac{1}{2} c'^S \frac{\partial e(\theta)}{\theta} \left(\frac{\partial e(\theta)}{\theta}\right)^S c'\right) c(z_s) \quad (6)$$

Following the integral calculation rule, Formula (7) can be divided into two portions for separate calculations. The first portion is simplified as:

$$\int_{-\infty}^{+\infty} O_\theta(z_s) * \left(c'^S \frac{\partial e(\theta)}{\theta}\right) c(z_s) = \left(c'^S \frac{\partial e(\theta)}{\theta}\right) * O_\theta (z_s) \int_{-\infty}^{+\infty} O_\theta(z_s) c(z_s) \quad (7)$$

The second part could potentially be expressed as Formula (8):

$$C_{LK} = \int_{-\infty}^{+\infty} O_\theta(z_s) * \left(c'^S \frac{\partial e(\theta)}{\theta} + \frac{1}{2} c'^S \frac{\partial e(\theta)}{\theta} \left(\frac{\partial e(\theta)}{\theta}\right)^S c'\right) c(z_s) = \frac{1}{2} c'^S * \int_{-\infty}^{+\infty} O_\theta (z_s) * \left(\frac{1}{2} c'^S \frac{\partial e(\theta)}{\theta} \left(\frac{\partial e(\theta)}{\theta}\right)^S\right) c(z_s) *= c' \frac{1}{2} c'^S \psi(\theta) c' \quad (8)$$

The Riemann metric of the statistical manifold at θ is $\psi(\theta)$, which characterizes the Fisher details received from $O_\theta(z_s)$, using Formula (9).

$$\psi(\theta) = \mathrm{F}_z \mathrm{r} \mathrm{O} \left[\nabla \mathrm{T}(\theta, z_j) \nabla \mathrm{T}(\theta, z_j)^S\right] \quad (9)$$

The natural gradient $\tilde{\nabla} T(\theta, z_j)$ can be estimated using the general ENGB as follows, by Formula (10):

$$\tilde{\nabla} T(\theta, z_j) = \psi(\theta)^{-1} \nabla \mathrm{T}(\theta, z_j) \quad (10)$$

This strategy improves signal feature extraction through TFA by using the ENGB technique, which aligns the Euclidean gradient with the statistical manifold of signal occurrences. To develop an enhanced technique for power signal processing based on TFA in the different phases below. Use θ^0 as the initial parameter vector for signal characteristics. Generate the signal feature z_j and its accompanying parameter vector θ_s^{n-1} iusing the ordinary gradient in the n^{th} iteration. To upgrade the parameter vector, determine the natural gradient $\tilde{\nabla} T\ (\theta_s^{n-1}, z_j)$ and, build a different set of base learners along this gradient. The update rule for parameters were expressed in equation (11):

$$\theta = \theta^0 - \beta \sum_{n=1}^{N} \alpha^n \beta^n \quad (11)$$

Here, θ^0 indicates the initial model parameters, and β represents the global learning rate. In the context of power signal processing, while the general procedure of power signal fluctuations is non-Gaussian, the suggests that each sample point should follow an electrical power system.

3.8 Short-time Fourier transform fused efficient natural gradient boosting (STFT-ENGB)

The STFT-ENGB hybrid is an integration of the STFT with TFA and ENGB to improve feature extraction in power signal processing. STFT segments signal to overlapping windows for comprehensive frequency and temporal analysis, whereas ENGB maximizes the extraction of signal features by matching gradients with the statistical manifold. The STFT-ENGB model achieves better signal processing strength, particularly when dealing with involved, non-stationary power signals. STFT-ENGB hybrid method used to perform better PQD because it uses both time-frequency analysis and machine learning models. STFT is the time-varying and localized characteristic of non-stationary power signals, hence appropriate when tracking transient and dynamic disturbances. ENGB increases the accuracy of the classification process by dealing with the non-linear and intricate patterns of the features. This combination guarantees a high detection rate, resistance to noises and applicability to different kinds of PQD. Moreover, the hybrid model was computationally efficient to allow monitoring in real time of the smart grid environment. Algorithm 1 shows the proposed STFT-ENGB model working procedure.

Algorithm 1: STFT-ENGB

```
import numpy as np
import pandas as pd
import scipy.signal as signal

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler
from lightgbm import LGBMClassifier

from sklearn.metrics import classification_report
X_signals = np.load("signals.npy")
y_labels = np.load("labels.npy")
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_signals)
def extract_stft_features(signal_data):
  features = []
  for sig in signal_data:
    f,t,Zxx = signal.stft(sig,nperseg = 128)
    power = np.abs(Zxx) ** 2
    mean_power = power.mean(axis = 1)
    features.append(mean_power)
  return np.array(features)
X_features = extract_stft_features(X_scaled)
X_train,X_test,y_train,y_test = train_test_split(
  X_features,y_labels,test_size = 0.2,stratify =
y_labels,random_state = 42)
model = LGBMClassifier(boosting_type =
'gbdt',n_estimators = 100)
model.fit(X_train,y_train)
y_pred = model.predict(X_test)
print(classification_report(y_test,y_pred))
```

4 Results

The proposed model's strategy and its applications in enhancing power quality monitoring through the integration of STFT-ENGB were described previously. This model effectively addresses disturbance detection by leveraging time-frequency feature extraction and adaptive boosting, offering a robust and real-time approach tailored to dynamic grid signal variations.

4.1 Experimental configuration

The system configurations with Python setups are employed for TFA is used to process power signals and extract features. The signal-piloted gain device acts as a triggering device which continuously checks the incoming power signals as per the occurrence of anomalies. It also triggers feature extraction and data acquisition when it recognizes an unusual variation in the regular activities. It was useful for avoiding the unnecessary data and efficiency of computation. Figure3 represents the Signal-Piloted Gain Device of Voltage Phase.

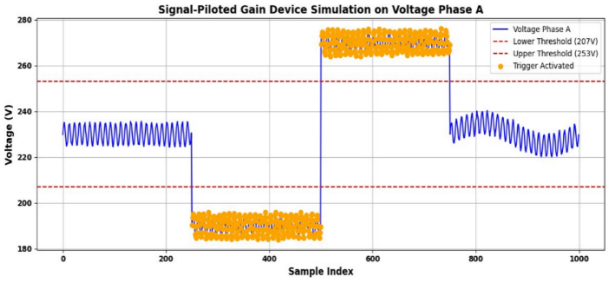


Figure 3: Signal-piloted gain device of voltage phase

The process can be implemented with a light-weight embedded microcontroller or digital signal processor

(DSP) and programmed with threshold-based detection algorithms. Hardware/software details was illustrated in Table 3.

Table 3: Hardware-software configuration for power signal detection

Component	Type	Details
Hardware Platform	Microcontroller / DSP	ARM Cortex-M series / DSP for real-time signal processing
Signal Input Interface	ADC (Analog-to-Digital Converter)	16-bit, high-speed ADC for sampling voltage and current waveforms
Triggering Logic	Comparator/Threshold Detector	Monitors signal amplitude/frequency changes to detect disturbances
Feature Extraction	Signal Processing Library	STFT implementation via CMSIS-DSP or similar optimized math libraries

4.2 Confusion matrix in power signal processing and feature extraction

Figure 4 depicts the confusion matrix for measuring the classification accuracy of a power signal processing model based on TFA. It indicates how accurately the model classifies four different classes, as labeled rows (True labels) and columns (Predicted labels). The diagonal values (74, 75, 75, and 69) represent the count of correct predictions for each class, which signifies that the model classifies with high accuracy. Where x – plane indicates the predicted label and y- plane indicates the True label. It was particularly useful for imbalanced datasets, where simple accuracy might be misleading. It assists in figuring out the model's operational efficiency and potential areas for improvement.

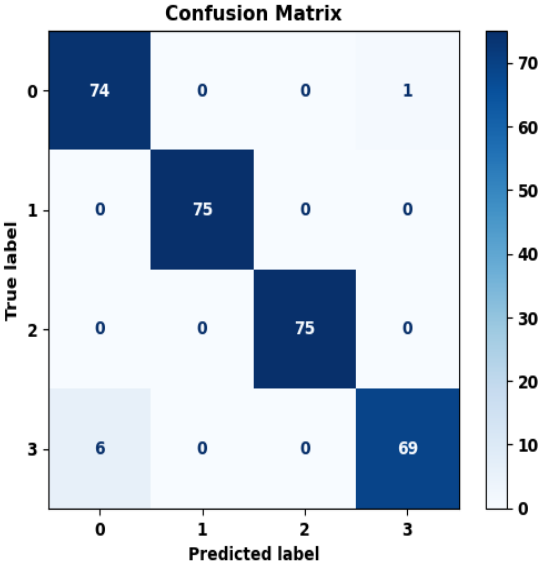


Figure 4: Confusion matrix showing classification performance for power signal processing using TFA

4.3 Current distribution and TFA across phases and classes in power signal processing

The analysis of the time series and distribution of current in Phase A among classes, emphasizes central predisposition and variability uniformity, as well as differences in oscillations between classes and phases. These characteristics are essential for power signal processing with TFA for efficient classification of different behaviors performed in STFT-ENGB.

4.3.1 Voltage distribution and TFA across classes in power signal processing using TFA

The voltage pattern and time series analysis of Phase A for varying classes show marked differences in the values of voltages, each with a distinct pattern for different classes. Such amplitude and phase differences are significant for feature extraction in power signal processing with TFA to discriminate operational conditions.

4.3.2 Voltage phase a distribution by class

Figure5 shows the distribution of voltage values for Phase A within four classes, which represent the IQR, with the median voltage value represented. This demonstrates that the different voltage values appear to vary widely across the classes. As an example, class 0 and class 1 appear to yield voltage values that are mainly between 220V and 240V. Here, the x- axis indicates the class label ranges from 0 to 3, and the y- axis illustrates the voltage (V) ranges from $180V$ to $280V$. It is important to recognize that the difference in voltage across the classes is important to differentiate between different operational states or behaviors, when the power signal processing model STFT-ENGB is based on TFA.

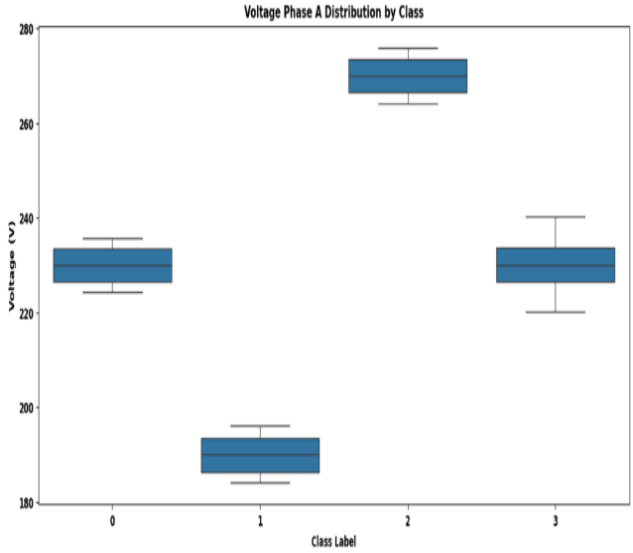


Figure 5: Voltage phase distribution across different classes in power signal processing using TFA

4.3.3 Voltage time series for each phase and class

Figure 6 shows the time series voltage for each phase (A, B, and C) in four classes (0 to 3) for the first 500 samples. Here, the x – plane illustrates the sample index, and y-plane indicates the voltage (V), ranges from $180V$ to $280V$. Each coloured line represents a class, and the oscillating patterns of voltage are noticeable across the three phases. Where, blue line depicts class 0, orange line indicates the class 1, green line depicts the class 2 and red line represents the class 3. The differences in voltage values in time across phases and classes can be leveraged for feature extraction from power signals using TFA, which can distinguish distinct operational states or operational behaviors, STFT-ENGB, depending on voltage discrepancies.

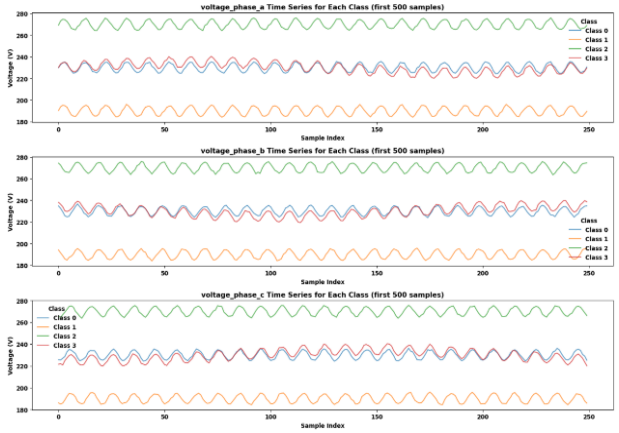


Figure 6: Voltage time series for each phase and class in power signal processing TFA

4.3.4 Current phase a distribution by class

Figure 7 presents the distribution of the current (in amperes, A) in Phase A, partitioned into four class labels. The interquartile range (IQR) is represented by each box, with the value of the median. This indicates that the central tendency and variability of the current values are fairly uniform between the classes. Where x –plane depicts the class label ranges from 0 to 3, and y- plane depicts the current in ampere (A), ranging from $8.5A$ to $11.5A$. This indicates that the central tendency and variability of the current values are fairly uniform between the classes. The data range, and there are no outliers, based on this analysis, the current in Phase A has comparable features for different classes and can be considered an important feature for the power signal processing model.

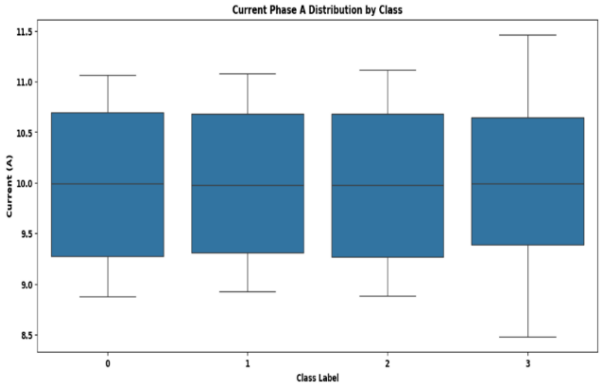


Figure 7: Distribution of current phase by the class label in power signal processing using TFA

4.3.5 Current time series for each phase and class

Figure 8 shows the existing time series for three phases (A, B, and C) of every class (0 to 3) using the first 500 samples. The time series of every phase is plotted separately, and every class is shown; the oscillations in the current are well apparent across all phases, and the amplitude and phase are slightly different between classes. The current phases a, band c was illustrated in Figure5. Here, the x – plane indicates the sample size, and y- plane indicates the current in ampere (A), ranges from $8.5A$ to $11.5A$. Where, blue line depicts the class 0, orange line indicates the class 1, green line represents the class 2 and red line represents the class 3. The TFA strategy can be employed to derive meaningful features distinguishing such classes efficiently to be classified in STFT-ENGB for further operations.

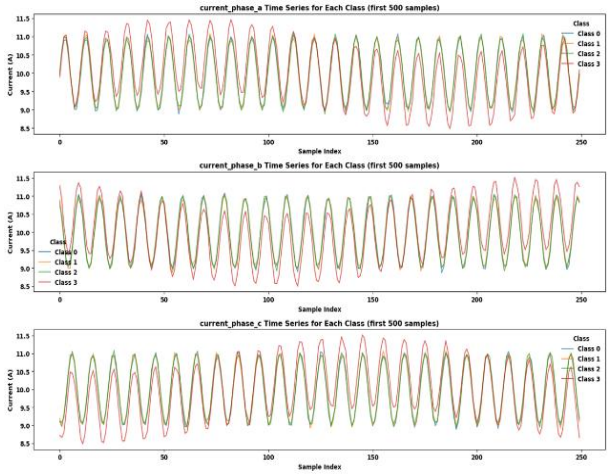


Figure 8: Current time series for each phase (A, B, C) and class in power signal processing using analysis TFA

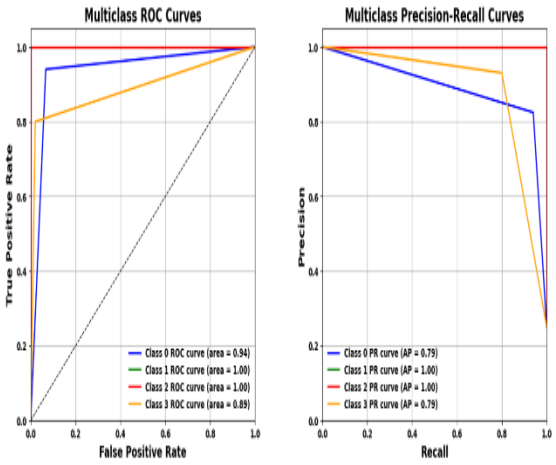


Figure 9: Multiclass ROC and precision-recall curves for power signal processing based on TFA

4.4 Multiclass ROC and precision-recall curves

Figure 9 shows both the multiclass ROC (receiver operating characteristic) curves and precision-recall curves for a power signal processing model from a TFA understanding. For the ROC curve, each class is plotted for the true positive rate (TPR) against the false positive rate (FPR). The ROC and PR curve discrepancies reveal the Classes 3 and 0 to perform, and the relative Classes 1 and 2 reveal intrinsic class level. In contrast, the classes 1 and 2 have perfect scores and represented in terms of features that were stronger and easily distinguishable. Class 3 and 0 predictions were negatively affected by noise or intra-class variability. In left side, it indicates the multiclass ROC curves and right side it represents the multiclass precision-recall curves. In multiclass ROC curves, the x-plane depicts the false positive rates and y- plane depicts the true positive rates. In multiclass precision-recall curves, the x- plane illustrates the recall score, which ranges from 0 to 1, and y-plane indicates the precision score, ranges from 0 to 1. These observations indicate that target data augmentation or class-by-class tuning.

4.5 Statistical test significance

The statically significance McNemar test yields a chi-squared statistic of 3.27 and a p-value of 0.0704, indicating an observed improvement that was not statistically significant at the 0.05 level. When the accuracy gain appears, it equates 7 correct classifications per 1,000 instances, which can be critical for timely and accurate detection of power quality disturbances in real-time smart grid environments.

The comparison of Training Time vs Inference Latency was illustrated, in Figure10. This plot shows a comparison between the training time and the inference latency of two models; SVM and STFT- ENGB. The fastest training achieved by SVM was 0.017s and the lowest latency of inference was 0.00044s, which suits light weight, real-time applications. STFT + ENGB took 1.223s to train, which is indicative of the more elaborate learning procedure and had low latency of 0.00123s. STFT-ENGB model was easy to train and hence the expensive training costs was less.

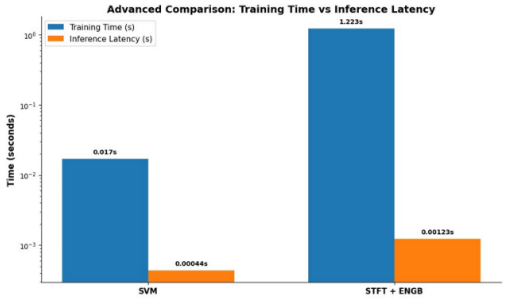


Figure 10: Training time vs inference latency

The scalability test enables to conclude the data point changes, and the training time increases with gradual changes; with 1.1 s size with 800--1000 samples increases gradually to 1.2 s, which proves its linear scalability. The inference latency is with 0.01 s size with 800-1000 samples increases gradually to 0.014 s, which proves its linear scalability, confirming the predictive potential of the model in real-time. These outcomes show that the STFT - ENGB model was effective and resistant to load. The scalability criteria and the real time feasibility used to accomplish power quality disturbances was illustrated in Figure11.

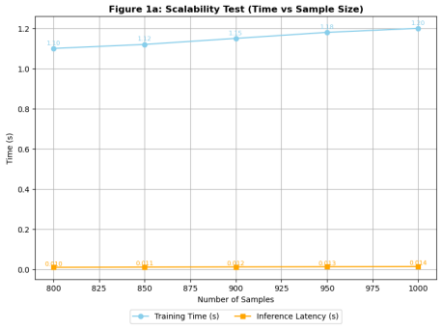


Figure 11: Output of scalability test

4.6 Metrics for evaluating the effectiveness of the proposed model

- **Accuracy:** Measures the overall rate of correct predictions. This indicator shows how successfully the system detects various categories of power quality problems within the smart grid setting

- **Precision:** It indicates how many actual positive cases exist within all the predicted positive outcomes. This metric helps the system to detect true PQD events correctly and the false alarms are kept at a low level.

- **Recall:** Measures the model's ability to detect all actual instances of a class. It attributes the strength exhibited by the model in response to different transient and fluctuation patterns of voltages.

- **F1-Score:** Balances precision and recall using their harmonic mean. The metric shows the balanced performance in real-time tradeoff between sensitivity and specificity.

The performance results of the proposed method are discussed in this section. The outcomes are contrasted with the other approaches, Support vector machine (SVM) [21], and Random Forest [22]. The Comparative performance of STFT-ENGB models, precision, F1-score, accuracy, and recall, was illustrated in Table 4 and Figure11.

Table 4: Comparative performance of STFT-ENGB models, precision, F1-score, accuracy, and recall.

Methods	**F1-Score (%)**	**Precision (%)**	**Accuracy (%)**	**Recall (%)**
SVM [21]	-	-	98.05	-
RF [22]	95.5	95.5	95.5	95.5
STFT-ENGB [Proposed]	**98.62**	**98.65**	**98.75**	**98.6**

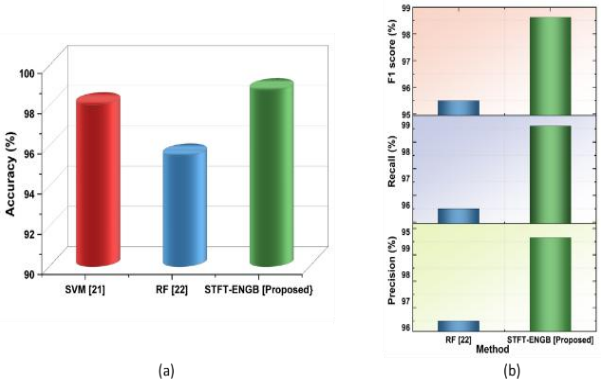


Figure 11: Evaluation of STFT-ENGB models, (a) accuracy and (b) recall, precision, and F1-score for enhancing power quality distribution detection.

The proposed STFT-ENGB approach is used for power quality monitoring through efficient time-frequency feature extraction and adaptive boosting classification. The system achieves an accuracy of 98.75%, showcasing its strong capability in correctly identifying power quality disturbances across various scenarios. With a precision of 98.65% and a recall of 98.6%, it reliably identifies disturbance patterns while minimizing false positives and missed events. Furthermore, the F1-score of 98.62% validates the model's robust and superior performance in a balanced way. These metrics validate that the STFT-ENGB approach has an effective solution for real-time smart grid disturbance detection.

5 Discussion

Power signal processing improves electrical grid and microgrid monitoring and control, particularly on the electrical grids due to more renewable energy. TFA methods might not sensitive enough to measure quickly, and the nonlinear nature of waveforms caused by power electronics-based renewable sources [15]. These techniques were frequently sensitive or flexible and it was desirable to observe faint or temporary perturbations in different loading conditions. The SVM model [21] based on power signal processing and feature extraction algorithm with TFA are its sensitivity to input data quality and levels of noise, which has performance metrics accuracy of (98.05%). The dependence of the model on pre-defined feature extraction methods can fail to completely reflect dynamic variations. RF models could involve heavy computations of building numerous decision trees, not suitable in real-time smart grid applications [22]. RF models have performance metrics accuracy of (95.05%), for modeling complex dimensional temporal dependencies in time-series PQD data. The RF algorithm can be affected by its performance when using imbalanced datasets in PQD settings. Furthermore, the effectiveness of the model highly relies on feature engineering and prevents the ability to adapt to unprecedented disturbances without retraining. Spectral leakage was commonly mitigated through windowing methods which minimize distortion in frequency analysis at the risk of sharp signal states. The cultured measures used to minimize leakage, used in real-time systems, might be heavier load on the delays. Feature robustness plays an essential role in excessive filtering to control leakage for accurate classification. The trade-off was extremely crucial in power signal analysis and smart grid applications.

To overcome these limitations, the suggested STFT-ENGB approach, incorporates adaptive noise reduction techniques for improved input data quality, providing better performance robustness. The algorithm employs real-time feature extraction using STFT to minimize computational burdens and capture dynamic changes effectively. The flexibility in STFT-ENGB makes it possible to fine-tune and verify it for a variety of power systems and operating regimes.

6 Conclusion

Power signal processing using the TFA method for evaluating non-stationary signals, which decomposes the signal into the transient system as well as frequency domains. TFA enables a composite representation of a signal's frequency spectrum over time, allowing it to efficiently record transient and time-dependent incidents. The dataset was collected from Kaggle. A normalization technique of z-score used for preprocessing the noise reduction. The power signals were subjected to discriminative, time-localized feature extraction using the STFT. To create a single representation, these extracted features were joined by using a late fusion technique. The STFT-ENGB model for enhancing the recognition of power quality disturbances with energy grid applications. Extensive experiments demonstrated that the proposed STFT-ENGB model outperforms baseline architectures, achieving superior results in terms of accuracy (98.75%), F1-score (98.62%), recall (98.6%), and precision (98.65%) to ensure the distribution of power qualities. These findings offer a promising solution for real-time power signal monitoring in smart grid environments, facilitating intelligent fault diagnosis and improving the overall resilience and responsiveness of modern electrical infrastructure. The TFA signal processing and feature extraction algorithm does not deliver the expected performance in the presence of noise and rapidly varying signals, or cannot be computationally feasible for systems with restricted resources. Future research can investigate the incorporation of sophisticated ML methods for the real-time processing of power signals, improving the efficiency and accuracy of feature extraction algorithms. The use of TFA-based algorithms in smart grid and

Internet of Things (IoT) applications has the potential to enhance energy management and fault detection.

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Research and Optimization of Charging Pile Demand Forecasting Model Based on Data Mining

Tao Jin[1]*, Bin Liu, Zhenqi Zhang
School of Information Eegineering, Yinchuan University of Science and Technology
*Corresponding author: chong214@163.com

Keywords: electric vehicle (EV), charging pile demand forecasting, infrastructure optimization, energy management, mandrill-tuned convolutional long short memory with auto encoder (MCLSM-AE)

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The rapid growth of electric vehicles (EVs) has led to a significant increase in the demand for accurate forecasting of charging pile usage, essential for optimizing infrastructure planning and energy management. Effective prediction models help to balance grid loads, reduce waiting times, and enhance the overall charging experience. Existing methods, based on traditional Machine Learning (ML) or basic neural network models, struggle to capture complex spatial-temporal relationships and multivariate dependencies. To address these limitations, this research proposes an advanced hybrid Mandrill-tuned Convolutional Long Short Memory with Auto Encoder (MCLSM-AE) framework that combines the Mandrill Optimization Algorithm (MOA), Auto Encoder (AE), and CNN-LSTM with an Attention Mechanism. The novelty of this approach lies in integrating MOA for optimal hyper parameter tuning, AE for dimensionality reduction and CNN-LSTM for spatial-temporal demand modeling, enhanced with an attention mechanism for improved interpretability. The model is trained on a dataset comprising historical EV charging data, traffic patterns, weather information, and spatial grid mappings. Preprocessing steps include data normalization and Missing Value Imputation (MVI) to ensure data quality. The proposed model workflow involves reducing data dimensionality with AE, extracting spatial patterns with CNN, and capturing temporal dependencies using LSTM, with MOA optimizing model parameters. Experimental results demonstrate the suggested MCLSM-AE model superior performance, achieving a MSE (0.00000000022) RMSE of (0.000014832), and MAE (0.0275) compared to existing methods. The research provides a robust and scalable solution for EV charging demand forecasting, addressing existing limitations and contributing to better infrastructure and energy management strategies

Povzetek: Študija je razvila hibridni model MCLSM-AE, ki združuje mandrillovo optimizacijo, AutoEncoder, CNN-LSTM in pozornost za napovedovanje povpraševanja po polnilnicah električnih vozil. Model učinkovito obdela prostorsko-časovne podatke ter doseže izjemno nizke napake, kar podpira optimalno energetsko in infrastrukturno načrtovanje.

1 Introduction

The Electric Vehicle (EV) sector has developed as the most important socially sustainable technology, with enormous potential for reducing carbon dioxide emissions while lowering dependency on oil [1]. EVs are a crucial solution for reducing the transportation sector's massive greenhouse gas emissions. The fast development of EVs is partly dependent on the building and arrangement of charging facilities [2]. The great amount of EVs associated with the grid creates an enormous strain on the electrical grid [3]. The rapid popularization of new Electric Vehicles (EVs), primarily its extensive promotion in various countries, relies heavily on the presence of charging facilities, like Charging Piles (CP), CP are a critical element in the period of electrified transportation, providing important fast charging service stations for new EVs, ensuring that daily travel demands are fulfilled and promoting the widespread adoption of EVs [4]. There are two categories of CPs such as DC quick charging and Alternating Current (AC) slow charging. The service style is self-pay and self-charge, and the locations are much more spread out than petrol stations [5]. Charging infrastructure has a huge impact on the growth of EVs due to its accessibility, dependability,

cost efficiency, smart networking, and environmental sociability [6]. However, inadequate charging services have developed as a key impediment for the EV sector. As EVs become more prevalent in urban areas, it is becoming more difficult to predict Charging Demand (CD) and plan for infrastructure [7]. To overcome the above challenges, the research proposed an advanced hybrid Mandrill-tuned Convolutional Long Short Memory with Auto Encoder (MCLSM-AE) framework that combines the Mandrill Optimization Algorithm (MOA), AutoEncoder (AE), and CNN-LSTM with an Attention Mechanism to develop a robust and scalable forecasting model for EVCP demand. This research offers a strong framework on EV charging demand prediction that may be utilized for better infrastructure development, grid load balancing, and user experience. For data-oriented policy and planning related to the long-term adoption of electric vehicle networks, it is especially beneficial for policy makers, utility companies, urban planners, and charging station operators.

The organization of the research contains the following sub divisions. Section 2 contains the related work and Section 3 explains the methods used to forecast the Electric VehicleCharging Demand (EVCD). The outcomes of the method were performed and discussed in Section 4. The research concluded in Section 5.

2 Related work

The research was compared with existing research as shown in the Table 1, which represents the summary of literature on EV charging demand forecasting.

Table 1: Summary of literature on EV charging demand forecasting

Ref. No.	Area Focused	Algorithms/Models Used	Result	Limitations
[8]	Urban EV quick charging demand forecasting	Regret Theory, Human behavior modeling, Data mining	Improved CD forecast accuracy using real ride-hailing data	Limited scalability due to localized data from Nanjing
[9]	EV public charging demand forecasting	Demand-supply stochasticity model, User heterogeneity modeling	High-resolution spatial-temporal forecasts	Assumptions in user behavior; uncertainty in future transport networks
[10]	EVCD forecasting under noisy data	CFMM-GEP (AutoEncoder + SVM + GEP)	Outperformed 6 models in MAPE, RMSE, MAE, R^2	Impacted by complex or irregular noise patterns
[11]	Charging station (CS) planning with multi-type CDs	Firefly algorithm, Roulette, K-Means, Markov Chain	Reduced cost and improved efficiency in real urban setting	Assumptions in user travel behavior; data uncertainty
[12]	Smart charging and private charging piles	Simulation-based modeling	Shifted peak load, improved charging profile	Based on one city's data; lacks generalizability
[13]	Automated charging infrastructure	1-to-N system, robotic arm, 2-layer iterative scheduling	Validated in real-time via hardware-in-loop experiments	High implementation cost; scalability issues
[14]	EV charging infrastructure deployment	Submodular functions, Erlang-loss, Lazy Greedy (LGDG & LGEG)	High efficacy and efficiency in site planning	May struggle in highly dynamic and complex environments
[15]	Smart EV-CP management system	IoT, K-Means, Multisim simulation	Reduced cost, improved voltage stability and user experience	Simulation-based validation only; needs real-world testing
[16]	Spatial-temporal distribution of EV load	Monte Carlo simulation	Showed distinct regional and	Requires detailed regional data; may not generalize globally

			temperature-based load variation	
[17]	EV charging prediction using UrbanEV dataset	DL models, Transformer, statistical models	Improved forecast accuracy	Regional focus (Shenzhen); potential bias due to geography/weather
[18]	Citywide EVCD prediction	CityEVCP (Hypergraph + POI clustering + Gated Transformer)	Outperformed baseline models in spatial-temporal accuracy	Scalability challenges in larger cities; POI data dependence
[19]	EV-CS position and capacity optimization	NSGA-II, Deep Learning, Queueing Theory	Enhanced efficiency, reduced waiting time	Difficulty estimating computational complexity; uncertain service rates
[20]	Short-term EVCD forecasting with private EVs	LSTM, compared with ARIMA, MLP	LSTM outperformed others (MAPE = 6.83%)	Prediction depends heavily on data interval and input structure
[21]	Short/long-term EVCD forecasting	Transformer, RNN, LSTM, ARIMA, SARIMA	Transformer achieved highest accuracy	Requires large data volumes for generalization and robustness

The existing model [8] was not scalable since it used Nanjing-specific data, and hence it would not be effective for other regions or large datasets. CFMM-GEP [10] contained complex or unusual noise patterns that influence the model's performance. The [14] method utilized submodular functions and Lazy Greedy algorithms to struggle with dynamic and complex environments; it might not be ideal for infrastructure deployment under dynamic conditions. Lastly, the method outlined in [19] that combined NSGA-II, deep learning, and queueing theory was facing the challenge of forecasting computing complexity and dealing with uncertain service rates, which can limit its performance in real-time optimization. To address these limitations, the research proposed an advanced hybrid MCLSM-AE framework.

3 Materials and methods

The research aimed to develop a robust and accurate forecasting model for the EVCD using the proposed advanced hybrid MCLSM-AE model. The model is trained on a dataset comprising historical EV charging data, traffic patterns, weather information, and spatial grid mappings. Data preprocessing includes data normalization and MVI to verify data quality. The MCLSM-AE method was used for predicting EVCD. The MCLSM-AE method design for prediction of EVCD is shown in Figure 1.

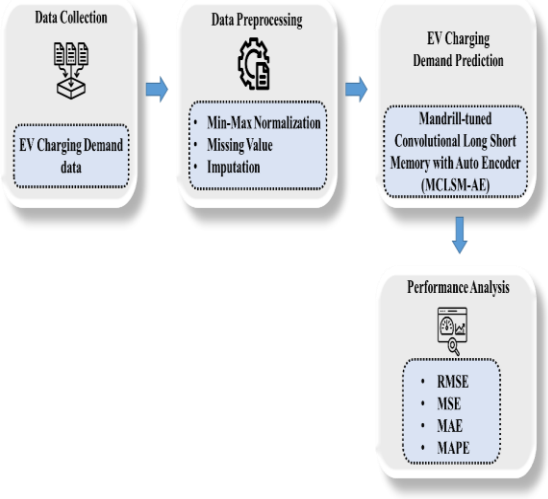


Figure 1: Structure for proposed framework to predict the electric vehiclescharging demand

3.1 Data collection

The data was gathered from Kaggle Link: https://www.kaggle.com/datasets/ziya07/charging-pile-demand-forecasting-dataset/data. The Charging Pile Demand Forecasting Dataset offers comprehensive information for forecasting how often electric vehicle (EV) charging piles will be used. This dataset contains a number of characteristics that affect the need for charging, including charging time, energy usage, traffic patterns, meteorological conditions, and geographic considerations. In order to accurately simulate real-world situations, it also takes into account variables like car type, charging station density, and

government incentives. The percentage of time spent using a charging pile is represented by the goal variable, charging_pile_usage_rate, which is essential for improving energy management and infrastructure planning in the expanding electric car market. By reducing wait times, balancing grid loads, and enhancing user experience, this dataset seeks to support the development of predictive models for effective EV charging stations. Table 2 show the overall dataset features. The data was split into testing and training with 80:20 ratio.

Table 2: Overall dataset features

Feature	Description
Charging Duration	Duration for which EVs use the charging pile (in hours).
Energy Consumed	Total energy consumed during charging (in kWh).
Traffic Flow	Number of vehicles passing through the charging station area.
Weather Conditions	Includes temperature, humidity, precipitation, and wind speed.
Geographical Information	Location-based features such as latitude, longitude, and distance to the nearest road.
Charging Price and Incentives	Charging price per kWh and availability of government incentives.

3.2 Data preprocessing

Data preprocessing is a process of converting raw data into an organized form that can improve the performance of the ML models. It facilitates the handling of inconsistency, noise, and missing values, resulting in consistent inputs for training. EV charging data were preprocessed by normalization using Min-Max Normalization and imputation using Multiple Imputation (MI). The Min-Max Normalization was applied to normalize EVCD data to the same range. MI was used to impute missing values that ensured completeness of data.

3.2.1 Data normalization

Data Normalization is used for normalizing numerical data into the standard range, typically between 0 and 1, thus allowing the different features of different magnitudes and different units not to dominate the process of model learning. Min-Max Normalization has been used in the normalization of the EV charging data. Min-Max Normalization is also employed to map historic EVCD data, traffic flow patterns, weather states, and grid space values onto the same scale. This approach applies the following Eq. (1).

$$Y_{new} = \frac{Y - min\,(Y)}{max\,(Y) - min\,(Y)} \quad (1)$$

Where Y is the old value, $max\,(Y)$ is the dataset's maximum value, $min\,(Y)$ is its minimum value, and Y_{new} is the new value derived from the normalized findings.

3.2.2 Missing value imputation (MVI)

MVI refers to the process of filling missing or incomplete data points with imputed values to maintain the integrity of the dataset. It ensures accurate EVCD forecasting by maintaining spatial-temporal data integrity despite missing records. MVI was applied using MI to deal with missing data-induced uncertainty and bias when EVCD is forecasted. The final parameter estimates, $\bar{\beta}$ are produced by pooling these values as given in Eq. (2).

$$\bar{\beta} = \frac{1}{n}\sum_{m=1}^{n} \hat{\beta}_m \quad (2)$$

Where $\bar{\beta}$ represents the final pooled parameter estimate, n is the number of imputed datasets, and $\hat{\beta}_m$ refers to the parameter estimates from each m^{th}imputed dataset.

3.3 Charging pile demand forecasting model using mandrill-tuned convolutional long short memory with auto encoder (MCLSM-AE)

MCLSM-AE integrates MOA's hyperparametertuning, uses CNNto extract spatial features, enabling such that the model can identify complex patterns in the data, and LSTM networks are utilized for extracting temporal dependencies, which are important in precisely predicting future EV charging demands. AE dimensionally compresses the data, which simplifies the data and makes the model more efficient by preserving only important features. This methodology maximizes the model's capability to estimate complex, multivariate, and spatial temporal demand patterns of EV CS. MOA was incorporated into MCLSM-AE to improve model performance by tuning parameters while AE's dimensionality reduction helpssimplify complex data and retain essential features. The combination helps make prediction performance reasonable in real-world scenarios, where functions have complex, non-linear relationships, and multiple influencing factors.

3.3.1 AutoEncoder (AE)

An AE is an unsupervised neural network that compresses input into lower-dimensional representations before reconstructing it to determine the quality of retrieved features. It is used to extract critical spatial-temporal elements from upstream and downstream EVCD data, hence improving forecasting accuracy. A function f is used to obtain the characteristic sequence of an original input sequence

$Y = \{y_1, y_1, \ldots, y_k\}$, where $y_i \in \mathbb{R}^d$. The output $T = \{t_1, t_2, \ldots, t_k\}$, where $t_j \in \mathbb{R}^l$, reflects the encoded properties of X. The encoder's output is provided to the decoder, which reconstructs the original data from T, resulting in $Z = \{z_1, z_1, \ldots, z_k\}$, where $z_i \in \mathbb{R}^d$. After training the AE, the encoder is used for feature extraction, revealing the data's underlying structure. Eq. (13) and (14) determines the encoding and decoding operation.

$$t_j = f(w_t \cdot y_j + c_t) \quad (13)$$
$$z_j = g(w_z \cdot t_j + c_z) \quad (14)$$

Where w_t, w_z, c_t, and c_z are weights and biases, respectively, and $f(\cdot)$ and $g(\cdot)$ are sigmoid functions. $y_j \in R^d$ is the original input vector of dimension d, the encoder weight matrix is given by w_t, and c_t is the encoder bias. $t_j \in R^l$ is the encoded feature from the encoder, the decoder weight matrix is w_z, and c_z is the decoder bias. Eq. (15) states that the AE is trained by minimalizing the reconstruction error.

$$L(Y, Z) = \frac{1}{2}\sum_{j=1}^{n} \left\| y_j - z_j \right\|^2 \quad (15)$$

This is a loss function calculates the rebuilding error between the input (y_j) and output (z_j). The Mean Squared Error (MSE) is calculated by over all n samples to ensure the encoder captures significant data characteristics. When the reconstruction error is sufficiently small, T is considered a valid representation of the original data.Let $Y_v = \{y_{v1}, y_{v2}, \ldots, y_{vm}\}$and $Yd = \{yd_1, yd_2, \ldots, yd_m\}$, where $y_{vj}, yd_j \in \mathbb{R}^d$, be the upstream and downstream charging load data. The characteristic sequence $x_t = \{x_1, x_2, \ldots, x_m\}$, with $x_j \in \mathbb{R}^l$, is calculated using Eq.(16) and (17).

$$x_j = f(w_z \cdot (y_{vj} + y_{ej}) + c_x) \quad (16)$$
$$z_j = g(w_z \cdot x_j + c_z) \quad (17)$$

$y_{vj} \in R^d$ are the upstream and downstream traffic flow vectors, w_z is the encoder weight and c_x is the bias. x_j is the encoded feature of combined traffic flow, w_z and c_z are decoder weights and bias. $g(\cdot)$is the sigmoid function producing the reconstructed output z_j, helping assess the effectiveness of the encoded features.

3.3.2 Convolutional long short memory with auto encoder (CLSM-AE)

The CLSM-AE combines CNN with LSTM and AE: CNN can be used to extract the specialcharacteristics, LSTM can be used to extract the temporal dynamics and AE can be used to boil down the dataset into lower dimensions. The capacity to extract both temporal and spatial characterizations with dimensional reduction offers a sound and powerful forecasting method for complex and high-dimensional patterns of EVCD in spatial-temporal situations.

3.3.3. Convolutional long short memory withattention mechanism

The model has two LSTM layers, an attention layer, single input layer, two convolution layers, and a single output layer. The input is first given to the model and the local characteristics are retrieved using CNN layers. The CNN layer's outputs are passed to the first LSTM layer to extract long-range relationships among variables. The attention layer leverages the hidden states of all LSTM layers to determine relevance for themselves. Finally, a weighted sum computes the output.

3.3.4. Convolutional neural networks (CNN)

CNN is a type of DL model that extracts spatial patterns and characteristics from data, such as images or grids. CNN is utilized to capture spatial dependencies in EVCD data, allowing for more accurate predictions by modeling the spatial distribution of CS and traffic patterns. The one-dimensional convolutional layer (Conv1d) receives the input $Y = \{y_1, y_2, \cdots, y_T\}$, which is specified by Eq. (3).

$$g_l = ELU\ (W_m Y + b_m) \quad (3)$$

Where g_l is m^{th} filter output, the activation function is represented by ELU, $W_m$is a matrix of weights and the bias vector is represented by b_m.

3.3.5. Long Short-Term Memory (LSTM)

LSTM is a type of Recurrent Neural Network (RNN) that predicts the long-term associations in sequential input. LSTM was utilized to describe the temporal dependencies in EVCD, allowing the forecasting model to consider historical charging patterns and more correctly estimate future demand over time. The outputs of the convolutional layers were given to the layer of the LTSM. There arethree gates, such as input, forget and output gate, and cell state. The forget gate removed some data in the first step and the input gate chooses which type of data is kept in the cell state, as shown in Figure 2. Eq. (4) to (6) provides the equations for these gates.

$$f_t = \sigma\ (W_f \cdot [g_{t-1}, \bar{y}_t] + b_f) \quad (4)$$
$$i_t = \sigma\ (W_i \cdot [g_{t-1}, \bar{y}_t] + b_i) \quad (5)$$
$$\tilde{C}_t = ELU\ (W_C \cdot [g_{t-1}, \bar{y}_t] + b_C) \quad (6)$$

Where g_{t-1} is represented as hidden state of $t-1$,forget gate is given by f_t, W is the weight matrix of the respective gate,$\bar{y}_t$ is the input of the layer in the time t, the bias of three gates is given by b,i_t is the input gate and C_t is the candidate value. The state of the cell at time t is depicted by the input gate $i_t$and C_t. Finally, the output gate (o_t) determines the current output as given by Eq. (7) to (9).

$$C_t = f_t * C_{t-1} + i_t * C_t \quad (7)$$

$$o_t = \sigma\left(W_o \cdot [g_{t-1}, \bar{y}_t] + b_o\right) \quad (8)$$

$$g_t = o_t * ELU\left(C_t\right) \quad (9)$$

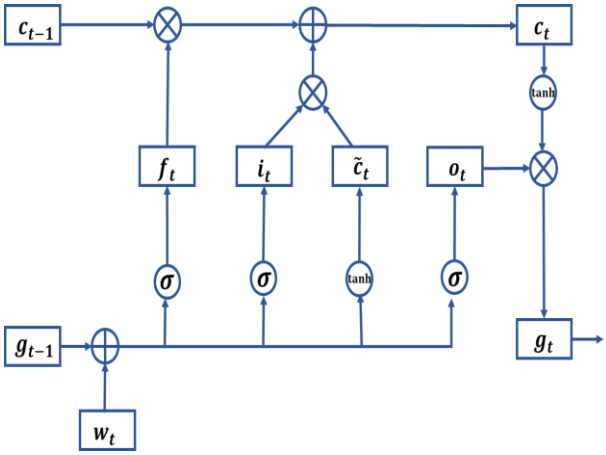


Figure 2: Architecture of LSTM

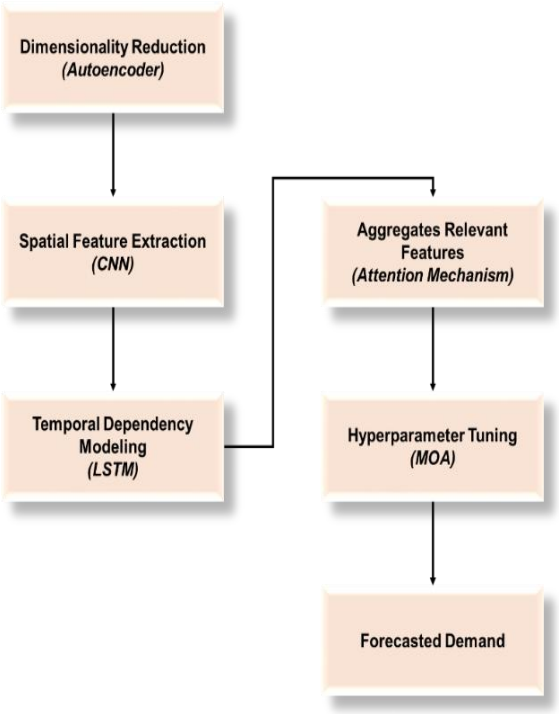


Figure 3: Structure of MCLSM-AE

3.4 Attention mechanism

The Attention Mechanism is a DL approach that allows the model to focus on significant parts of the input data, weighting relevant characteristics and ignoring less important features. It was utilized to prioritize crucial spatial-temporal information in EVCD forecasting, resulting in improved accuracy and interpretability. After the LSTM layers have pulled out the long-term dependences from the features, it will take their output and use it as input for the attention layer. The necessary equations are as follows in Eq. (10) to (12).

$$a_t^k = \frac{exp\ d_t^k}{\sum_{j=1}^{n} d_t^j} \quad (10)$$

$$d_t^k = v_d^T \sigma\left(W_e\ [g_{t-1}, c_{t-1}]\ + U_d g_t + c_d\right) \quad (11)$$

$$\bar{z}_t = \sum_t^T a_t^T\ g_t \quad (12)$$

The variables v_e,$c_d \in R^T$, $W_e \in R^{T \times m}$ and $U_d \in R^{m \times m}$was learned, while m denotes the number of neurons, the output of the attention layer utilizing a weighted sum of all the hidden states is $\bar{z}_t$, and the attention weights of the k^{th} input at time t are denoted by $a_t^k$and d_t^kdenote the significance of the g_t. The structure for the CLSM with Attention Mechanism was illustrated in Figure 3.

3.5. Mandrill optimization (MO)

MO is a swarm intelligence-based metaheuristic inspired by mandrills' natural social structure and behavior. It is used to improve the spatial-temporal EVCD forecasting model by balancing exploration and exploitation for higher prediction accuracy. The particles are represented as a matrix with each row representing a particle's whole location as given by Eq. (18), where d is the amount of dimensions and n is the total amount of mandrills.

$$P = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,d} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,1} \\ \vdots & \vdots & \cdots & \vdots \\ p_{n,1} & p_{n,2} & \cdots & p_{n,d} \end{bmatrix} \quad (18)$$

The technique of calculating and changing these places is described in mathematical terms. Initially, these places are produced semi-randomly and this process known as the initialization stage. Once each particle is allocated a place and, as a result, a fitness value, the positions are updated using the mathematical model of hierarchical dominance observed in mandrill hordes. The objective function F(x), optimized by the Mandrill Optimization Algorithm, is defined as the Mean Squared Error (MSE) computed on the validation set predictions during training.

3.6 Initialization phase

During this phase, research provides a semi-greedy initialization strategy. The first dimension of the search space is split into segments equal to the number of particles, guaranteeing that each particle is assigned to a unique segment along this dimension. For the remaining dimensions, particle placements are given at random, bringing variation to the starting population.

3.7 Dominator assignment

The next stage is to identify the dominator of each mandrill in the horde. Dominator assignment replicates the mandrill social hierarchy by ranking particles according to fitness values. To imitate this, research builds a parameter named α, which decreases linearly from 1 to 0 as the optimization process progresses. The equation for calculating α is given by Eq. (19).

$$\alpha = 1 - \frac{current\ iteration}{max\ iteratiatin} \tag{19}$$

As a result, as iterations pass, the chance of a child being ventral reduces as given by Eq. (20) and the attendance rate $B(t)$ at iteration t is computed using the following Eq. (21).

$$ventrality\ =\ \alpha < random\ (0,1) \tag{20}$$

$$B(t)\ = M \times \lfloor L + (U - L) \times \alpha \rfloor \tag{21}$$

The percentage of male participants at iteration t is given by $B(t)$, whereas L and U are the lower and upper bounds. This is mathematically expressed as follows: Eq. (22).

$$P_j = \frac{f_k}{\sum_{k=1}^{n} f_k} \tag{22}$$

The chance of the j^{th} mandrill winning the competition is represented by P_j, the fitness value of the j^{th} mandrill is represented by f_k, and the number of male mandrills competing is represented by n.

3.8 Finding radius vector

The velocity or ideal distance of a particle is essential for updating its location. In this suggestion, the term radius refers to an ellipsoidal-based method for creating points. Finding the ideal radius vector throughout the space's dimensions is essential to the algorithm's performance, as given by Eq. (23).

$$D_{p_j} = \sqrt{\sum_{k=1}^{d} \left(P_{d_j} - P_{p_j}\right)^2} \tag{23}$$

The dimensionality of the solution space is indicated by d, while the $\boldsymbol{U}$-th dimension of the dominator and the i-th position of the particle are represented by P.

3.9 Ellipsoidal new solution generation

The ellipsoidal new solution generation mechanism is an innovative technique for solution generation inside metaheuristic optimization algorithms. This technique increases the algorithm's durability as the ellipsoid is completely encompassed within the hypercube defined by the same distance vector (radius vector). The ellipsoidal technique removes superfluous areas for fresh solution generation from the hypercube as provided by Eq. (24).

$$(x - c)^T A^{-1} (y - c) \leq 1 \tag{24}$$

Where B is a positive-definite shape matrix, c is the center of the ellipsoid, and y is the candidate solution vector. The MCLSM-AE model has a unique benefit in EVCD forecasting by appropriately incorporating both spatial and temporal dependencies by utilizing CNN and LSTM components, respectively. The result is extremely accurate and robust predictions that are beyond existing techniques. Algorithm 1 depicts the Pseudocode for the MCLSM-AE model.

Algorithm1: MCLSM-AE)

Input:
- *Objective function* $F(x)$
- *Number of mandrills* (n)
- *Dimensions of the search space* (d)
- *Lower and upper bounds of search space* (L, U)
- *Maximum number of iterations* (Max_iter)

Output:
- *Best solution found* (X_best)
- *Best fitness value* (F_best)

Step 1: *Initialize the position matrix* $P\ [n \times d]$ *using semi* $-$ *greedy strategy*:
  For $i\ =\ 1$ *to* n:
    Set $P[i][0]$ *to segment* i *of dimension* 1
    For $j\ =\ 1$ *to* $d - 1$:
      Set $P[i][j]$ *randomly in* $[L[j], U[j]]$

Step 2: *Evaluate initial fitness* $f_k = F(P[k])\ \forall\ k\ \in \{1, 2, \ldots, n\}$

Step 3: *For* $t\ =\ 1$ *to Max_iter do*:

Step 4: *Update alpha* (α) *using Eq.* (19):

Step 5: *Compute attendance rate* $B(t)$ *using Eq.* (21):

Step 6: *Assign dominators*:
  Sort all mandrills by fitness $(ascending)$
  Assign top $B(t)$ *mandrills as dominators*

Step 7: *For each mandrill* $j\ =\ 1$ *to* n:

Step 8: *Evaluate ventrality using Eq.* (20)

Step 9: *Select a dominator* (*based on P_j in Eq.* 22)

Step 10: *Calculate Radius Vector D_pj using Eq.* (23):

Step 11: *Generate ellipsoidal new solution y using Eq.* (24):

Step 12: *If y is inside bounds* $[L, U]$:
  Evaluate fitness $f_y\ =\ F(y)$
  If $f_y < f_j$:
    Replace $P[j] \leftarrow y$
    $f_j \leftarrow f_y$

Step 13: *End For*

Step 14: *Update global best*:
If any $f_j < F_best$:
$X_best \leftarrow P[j]$
$F_best \leftarrow f_j$
Step 15: *End For*
Return X_best, F_best

4 Result

The main aim of the study was to create a reliable and close forecasting model for EVCD based on an MCLSM-AE model. This section contains the description of the experimental setup, and prediction metrics used to predict the EVCD.

4.1 Experimental setup

The experimental setup was executed in Python with the TensorFlow and Keras libraries on a PC system with an Intel Core i7 processor, NVIDIA RTX 3080 GPU and 32GB RAM. The models were tested and trained on a 1TB SSD storage with Windows 11 to help manage data efficiently and make it more efficient to perform computations.

4.2 Outcome of performance metrics

The performance metrics used to forecast the EVCD, such as convergence curve, and charging time prediction time.

4.2.1 Convergence curve

The convergence curve shows how the optimization process reduces the loss or error along iterations. It shows the efficiency and strength of the model training process in attaining optimal EVCD forecasting performance, as illustrated in the Figure 4.The convergence curve of the MCLSM-AE model displays a precipitous decline in fitness from the initial level of approximately 1.72×10^6 to the terminal value of approximately 1.24×10^6 in the first 40 iterations, which shows efficient optimization and faster convergence compared to usual methods, and confirms the high-level learning and predictive power of the MCLSM-AE in EVCD forecasting.

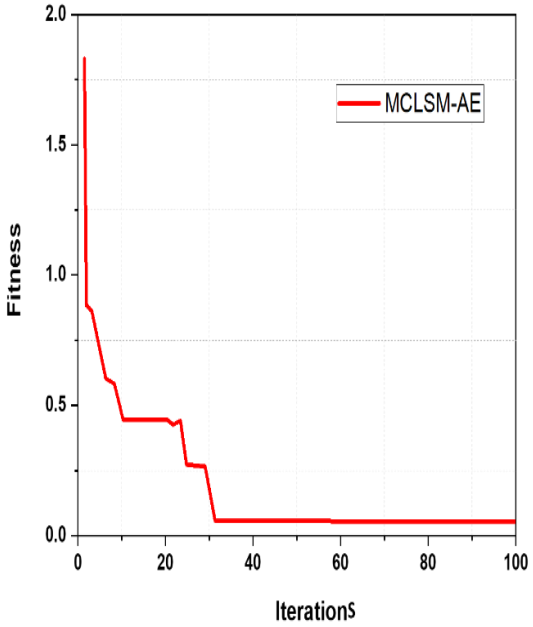


Figure 4: Convergence curve for EVCD Forecasting

4.2.2 Charging demand forecasting time

Charging demand forecasting time refers to the time a forecasting model takes to precisely predict future EVCD using the historical and real-time information. It is essential to facilitate timely energy distribution, grid operation optimization, and removal of charging delays in smart city infrastructures. Visual representation of the charging demand forecasting time was illustrated in Figure 5.

Fig.5 shows the forecasted charging demand over time by using the MCLSM-AE model, which begins at 10 units and increases smoothly to 65 units for a 4-hour period. The curve shows that the model can reproduce the nonlinear trend of increasing growth in CD accurately.

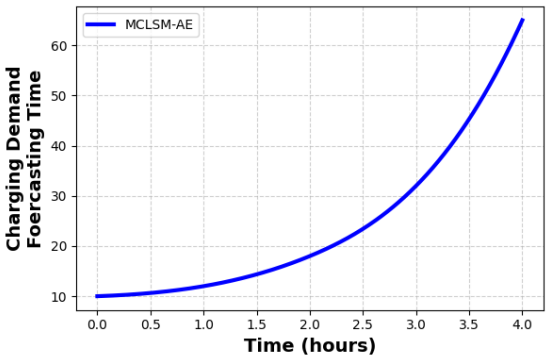


Figure 5: Charging demand forecasting time

4.3 Comparison phase

In this segment, performance indicators like Mean Absolute Error (MAE), RMSE, Mean Absolute Percentage Error (MAPE) and MSE to predict the EVCD using MCLSM-AE model. MCLSM-AE was compared to base models which are already present such as empirical mode decomposition with arithmetic optimization algorithm and deep LSTM combined (EMD–AOA–DLSTM) [22], PAG [23] and Fusion graph convolutional network with enhanced gate recurrent unit and Red Kite Optimization Algorithm (FGCN-EGRU-RKOA) [24], which all were used for prediction of EV charging demand.

4.3.1. Mean absolute error (MAE)

MAE computes the average magnitude of errors between predicted and actual values irrespective of their direction. It was utilized to measure the accuracy of EVCD predictions, which helps in determining how well the MCLSM-AE's predictions compare against actual values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (1)$$

4.3.2. Root mean square error (RMSE)

RMSE provides a simple evaluation of the amount of the model prediction error by quantifying the square root of the average of squared discrepancies between actual and forecasted values. Lower RMSE illustrates better generalizability and predictability.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (2)$$

4.3.3. Mean Squared Error (MSE)

MSE is a mean of the squared errors between the expected and the real values, giving more importance to important errors. Lower MSE means the model is effectively minimizing prediction error in training and validation.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (3)$$

4.3.4. Mean absolute percentage error (MAPE)

MAPE analyzes the average total percentage error between the projected and the real data to yield a normalized error measure. It is particularly valuable for assessing forecast precision at various EV charging load demand levels. A lower MAPE value shows that the forecasting model is stronger and relevant to real-world applications.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \vec{y}_i}{y_i}\right| \quad (4)$$

Figure 6 illustrates the graphical representation of RMSE and MSE using the MCLSM-AE model for EVCD prediction. The EMD–AOA–DLSTM [22] approach reported an RMSE of 0.000020628 and MAE of 0.1083, which shows relatively higher errors than the other approaches. The PAG [23] approach gave much better results with an RMSE of 0.0548 and MAE of 0.0333, displaying improved accuracy. The FGCN-EGRU-RKOA approach gave moderate results with an RMSE of 0.1735 and MAE of 0.3228. Conversely, the MCLSM-AE had excellent performance with RMSE of 0.000004 and MAE of 0.0275, superior to that of all the other models, which also showed its high accuracy and reliability in the forecasting task. Table 3 shows the RMSE and MAE of MCLSM-AE for EVCD prediction.

Table 3: RMSE and MAE values of the MCLSM-AE model for EVCD prediction

Methods	RMSE	MAE
EMD–AOA–DLSTM [22]	0.000020628	0.1083
PAG [23]	0.0548	0.0333
FGCN-EGRU-RKOA [24]	0.1735	0.3228
MCLSM-AE [Proposed]	0.000014832±0.00 00012	**0.0275**±0.0 011

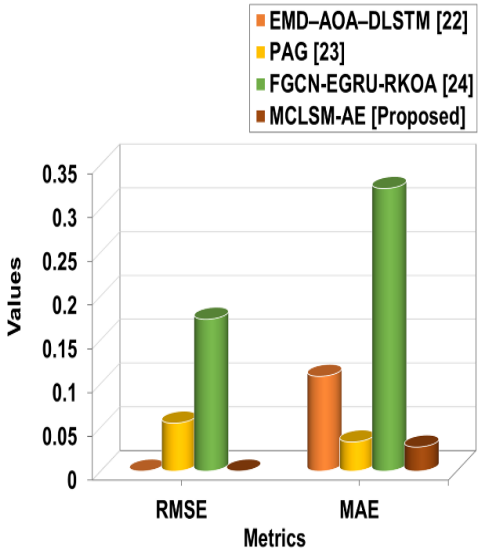


Figure 6: Graphical Representation of RMSE and MAE using MCLSM-AE model for EVCD prediction

Table 4 and Figure 7 show the model evaluation of MSE for MCLSM-AE with the existing method. The MCLSM-AE method demonstrates superior performance with an MSE of 0.0000015, while the other methods, such as EMD–AOA–DLSTM [22] (0.00004255) and FGCN-EGRU-RKOA [24] (0.0301), show comparatively poor results.

Table 4: Model Evaluation Table of MSE for MCLSM-AE with Existing Method

Methods	**MSE**
EMD–AOA–DLSTM [22]	0.00004255
FGCN-EGRU-RKOA [24]	0.0301
MCLSM-AE [Proposed]	0.00000000022±0.000000000 05

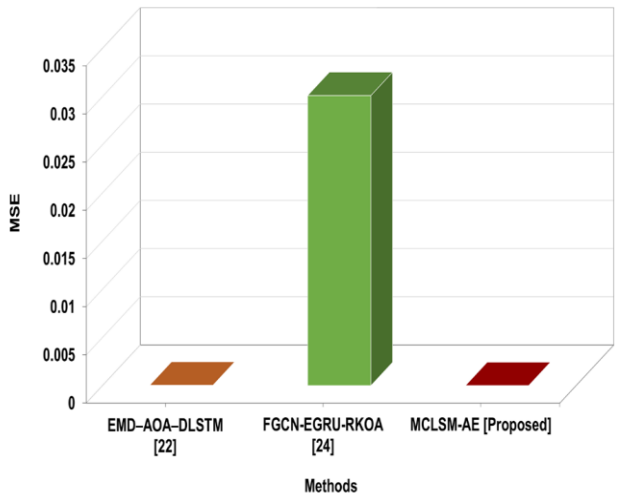


Figure 7: Performance Comparison of MSE across Different Models for EVCD Prediction

Table 5 and Figure 8 illustrate the MAPE-based performance comparison between PAG and MCLSM-AE models. The proposed MCLSM-AE model achieves a lower MAPE of 0.0934, compared to 0.1687 for the PAG [23] method, indicating improved accuracy.

Table 5: Summary of the MAPE value for the MCLSM-AE

Methods	**MAPE**
PAG [23]	0.1687
MCLSM-AE [Proposed]	**0.0934**±0.0043

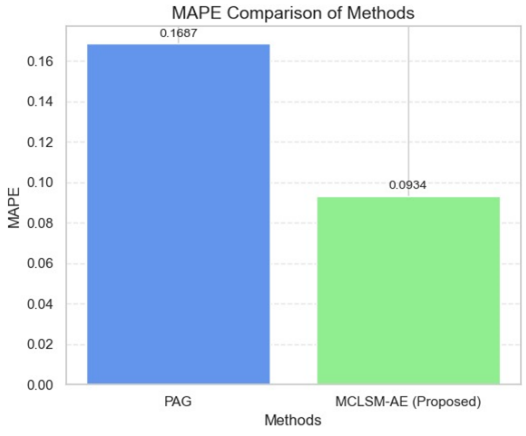


Figure 8: MAPE-Based Performance Comparison between PAG [23] and MCLSM-AE

Figure 9 depicts the 5-fold cross validation and average values facilitating more effective energy distribution and infrastructure planning.

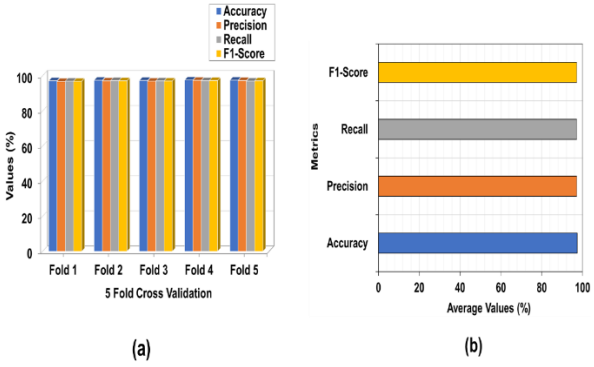


Figure 9: Outcome of (a) 5-Fold Cross Validation (b) average values

4.4 Discussion

The MCLSM-AE approach has a lower MAPE of 0.0934, which shows better accuracy in prediction than the PAG [23] approach with a MAPE of 0.1687. The research proposed an advanced hybrid MCLSM-AE model to predict the EVCD. There are some limitations of existing models like EMD-AOA-DLSTM [22], PAG [23], and FGCN-EGRU-RKOA [24]. EMD-AOA-DLSTM [22] and FGCN-EGRU-RKOA [24] have high RMSE and MAE values, reflecting poor accuracy and ineffective noise and spatial-temporal dependency handling. Model like PAG [23] does not provide holistic error reporting, which degrades the evaluation quality. However, MCLSM-AE achieves a better performance compared to the below models with least RMSE, MAE, and MSE, indicating higher precision. Its strong robustness, noise resistance, and dynamic learning provide a better solution to actual real-world CD of EVs. The MCLSM-AE model greatly improved the EVCD prediction accuracy, facilitating more effective energy distribution and infrastructure planning. This helps in more intelligent grid management and sustainable development of electric mobility.

5 Conclusion

The MCLSM-AE model was successfully developed and validated for estimating EVCD with the introduction of the MOA, AE, CNN-LSTM, and attention mechanism. The model was successfully trained on a dataset comprising historical EV charging data, traffic patterns, weather information, and spatial grid mappings. The model addressed complex spatial-temporal patterns and noisy behaviors by applying rigorous preprocessing methods, including normalization, MVI, and feature reduction. The implementation of MOA allowed for intelligent hyperparameter fine-tuning, while CNN and LSTM captured spatial and temporal trends, respectively. The model outperformed baseline methods, decreasing with a reduced RMSE of 0.000004. However, the research was limited by the availability and quality of real-time charging and traffic metrics, and the model's generalizability across regions was not properly validated. Future research could focus on real-time adaptive learning, integration with Renewable Energy (RE) sources, and deployment in a variety of urban settings to improve the scalability and effectiveness of the EV infrastructure planning and the energy management. Future work focuses on incorporating these tests to rigorously validate the improvements of the proposed model over baseline methods.

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Reverse-Time Event Sequence Prediction Using Summary Markov Models and Denoising Diffusion Processes

Jiao Wu
School of Computer Engineering, Shangqiu University, He Nan, Shang Qiu, 476000, China
E-mail：wujiao555888@126.com

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Choosing a suitable subset of the event information is the first step in using the framework. We are unable to provide assistance with this endeavor since it is very customized and requires creativity. With any luck, the event data will be adequately represented by a probabilistic framework that is fitted using a learning algorithm once a dataset has been constructed. The algorithm's output is a representation suitable for use in prediction. This can only be achieved by feeding the framework event data from execution process instances. With the use of the probabilistic model, we can assess the chances of the procedure continuing using various event sequences given the current sequence of occurrences. Specifically, this feature may be used to foretell the process's continuation-inducing event type with the highest probability. Verifying that the prediction model does not go against common sense is something a framework user may want to undertake. The first step of this study is to use a transformation method to derive the conceptual framework from the probabilistic model. It is possible to see and understand this conceptual paradigm. A user may check how well the model matches his expectations. The outcome would depend on his expectations; he may find behavior that goes against them or decide that the probabilistic framework is sufficient. In the second scenario, a problem analysis might be conducted to determine whether the expectations were incorrect or if the probabilistic framework is insufficient. When the model's transformation algorithm produces a conceptual model that is too complicated for humans to understand, the framework offers algorithmic assistance to those who need it. To be more specific, one may utilize model query techniques to check for certain patterns in the model. The user's expectations on the presence or absence of model structure may be represented by the patterns. Any model, no matter how complicated, may be tested through comparing this expectation to the query results. The capacity of Markov Chain Models is used to handle sequential data—that is, to "remember" information from earlier events in the sequence as they go backwards through time—makes them ideal for reverse time prediction. Finally, we evaluate the order model (or memory) of time series related to electrocorticographic (ECG) data recorded epileptic episodes by making use of the latter attribute. Improved prediction accuracy and correlation efficiency are the results of a novel method that merges estimates from forward predictors and backward predictors. We prove that events may be informed by changes on Markov Chain Systems by analyzing dynamic graphs built from time-series data, i.e., time-series fluctuation. In a stochastic model known as a Markov chain, the previous state is irrelevant to determining the subsequent state; instead, the present state is used exclusively. This served as inspiration for the suggested encoding technique, which aims to provide accurate and interpretable predictions of time-series events. In a process that is fundamentally inverted from the conventional Markov chain prediction, the conditional likelihood of the prior state is computed given the present state. The experimental findings from five real-world datasets demonstrate that our method outperforms baselines and offers other explanations for the outcomes of event prediction.

Povzetek: Študija uvaja pristop obratnega napovedovanja zaporedij dogodkov z združevanjem povzetkovnih Markovih modelov in difuzijskih postopkov. Metoda izračuna verjetnosti preteklih stanj glede na trenutno stanje, izboljša napovedovanje časovnih serij in preseže primerjalne modele na petih realnih podatkovnih zbirkah.

1 Introduction

The goal of sequential event prediction is to forecast the subsequent event in a current event sequence by using a "sequence database" of previous event sequences as a learning resource [1], [2]. We concentrate on applications where the collection of historical occurrences, rather than the precise sequence of those occurrences, has predictive potential. These kinds of applications may be found in medical informatics, equipment maintenance [3], [4], recommender systems, and other fields. Forecasting

purchase timings, transaction patterns, and social media activity are just a few of the numerous real-world uses for sequence prediction. Since the challenge entails the difficult job of concurrently modeling two difficult data types—categorical data for event categories and strictly positive continuous data for inter-arrival times—it calls for a specialized model [5], [6]. Our method improves efficiency and performs noticeably better than current baselines for long-term forecasting. Our experimental research sheds light on how the model does this, showing that it is more effective at forecasting distant events and can capture more intricate association patterns. The objective is to guess the remaining (hidden) events in the sequence using the set of disclosed events—not necessarily their order. To create the forecasts, we may consult a "sequence database" of historical event sequences [7]. Every time a new event is announced, predictions for the next one are updated. Sequential prediction issues have numerous instances. Medical illnesses develop throughout time, and those that a patient has already encountered might be utilized to forecast future problems. The time-series prediction issues that one may solve using a Markov chain are not the same as the sequential event prediction problems that we examine here [8], [9]. For example, there is no inherent order in the online grocery shop recommender system dilemma about which items should be put to the basket, and the order of the addresses is probably not very important when it comes to email recipient recommendations [10], [11]. The remaining sequence can only be predicted with the set of previous elements. We approach the sequential event prediction process as a supervised ranking problem at each stage [12], [13]. Our algorithms rate all other potential events based on their probability of becoming a following event in the sequence, given a set of disclosed events from the present sequence. How far down the list we must search to locate the next item or items to be added determines how accurate our forecast is [14], [15]. A substantial body of literature has focused on solving these problems, which include complicated relationships (e.g., geographical, temporal, and semantic), heterogeneous multi-faceted outputs, and streaming data feeds. Since event prediction issues are highly multidisciplinary, the majority of current event prediction techniques were developed to handle particular application domains [16]. However, the concepts and evaluation processes used are often applicable to other domains as well. In the lack of an exhaustive literature review for event prediction, however, cross-referencing the methods across domains is both necessary and challenging [17]. Much effort has been put into developing and using event prediction techniques in order to tackle these problems in recent years. Though event prediction methods are often still in their early stages, there has been a recent upsurge of research that suggests and implements novel ways across several domains [18]. Although most current event prediction systems have been developed for particular use cases, their underlying principles are often generic enough to address issues in other use cases as well. Regrettably, it is challenging to use these methods in varied contexts for different groups. The unique characteristics of the subject matter necessitate complex and purpose-built evaluation strategies to ensure high-quality event prediction results. These features include, but are not limited to, the fact that the subject matter is multi-objective (e.g., focused on accuracy, resolution, efficiency, while lead time) and that the prediction results are heterogeneous (e.g., with multiple outputs). Unfortunately, there are currently no methods for systematically standardizing and summarizing the several suggested event prediction models.

1.1 Challenges

- **Data sparsity:** Precisely predicting the chain of events that leads to a given result may be challenging in the absence of sufficiently rich data.
- **Events association:** While the model is good at seeing patterns of association, it isn't perfect at capturing the linkages that really drive the events.

Within seconds, contemporary network settings produce a massive amount of network events. Consequently, there is a lot of labor involved in analyzing network events, especially when there are a lot of collected network variables. It is essential to convert the information into time series forms with equal intervals in order to examine data from time series network events. A huge number of streaming intrusion signals were previously analyzed using aggregation [6]. Nevertheless, due to the large number of events occurring at time *bit*i, the aggregation method used to time-stamped events can be prone to significant variance. To better predict when a network will be healthy or under assault, we provide a method that can transform several sequences of network activity into time series representations. In particular, our strategy applies statistical measures and computational approaches to transform network events into time series data over a desired time scale, allowing us to extract temporal properties. When representing data with several dimensions in a two-dimensional space, PCA is a common dimension reduction method used in visualization. All data instances are mapped into the x- and y-axis of the 2D space using the first and second main components that are calculated. By using the Fisher-Jenks algorithm, also known as Jenks' natural breaks categorization approach, to create clusters, the predicted network events may be more accurately represented. The optimal classification of values into several groups is found by it. Three separate groups were established from the various normal and assault occurrences via the use of a categorization procedure. Our suggested technique is shown to be successful in detecting attack patterns and projecting

probable future assaults using a publicly accessible network traffic dataset acquired in a honeypot system. We tested two-time scales for network attack event prediction and attacker temporal pattern understanding to find out how well they worked. To further test the efficacy of our suggested method, we conducted a battery of data analysis. Ultimately, this research adds the following to the existing body of knowledge:

- A state-of-the-art method for extracting time-related characteristics from network events is presented, which combines statistical measures with wavelet transform and permutation entropy. Additionally, we provide an innovative approach to retrieving time-related characteristics from categorical information pertaining to network traffic.
- The suggested method's efficacy is assessed by performance evaluations with varying time scales (Zs=60ts=60 and 120 s).
- The characteristics are evaluated and numerous outputs (such as network normal along with attack events) are forecasted using DL.
- The efficacy of evaluating network events using the retrieved temporal characteristics is determined by visual analysis using several visualization approaches.

In Section 2 of this publication, the relevant work is described. Section 3 follows with an explanation of our methodology and the dataset consisting of network traffic. Section 4 presents the outcomes of the experiments. Finally, Section 5 and Section 6 cover the study's and future research's implications.

2 Related works

The focus of the study conducted by the authors of [19] is on analyzing the performance of different machine learning algorithms using recorded EEG data. The goal of that research is to identify the optimal model for use in developing an ensemble model to enhance learning. Logistic regression, the Naive Bayes model, and the K-nearest neighbors Random Forest are examples of traditional machine learning approaches; artificial neural networks, convolutional neural networks, autoencoders, and long short-term memory are examples of deep learning techniques. When comparing the sensitivity and specificity of all the models in that investigation, Random Forest with Long Short-Term Memory stood out.

That study systematically examines the impact of varying noise levels on the accuracy of forecasting of different load components and compares four recurrent neural network frameworks [20]. When it comes to horizontal bending moment and torsional moment prediction, the GRU network excels, whereas the LSTM network excels in vertical bending moment prediction. Despite applying filters to the initial noise information, the prediction accuracy continued to decline with increasing noise levels. In comparison to the torsional moment, the vertical and horizontal bending moments are better at predicting future behavior.

Finding an efficient method for handling time series data with missing values and volatility is the goal of the authors of [21]. For accuracy evaluation, they used RMSE, and to estimate execution time, they used the Python Timeit module. According to the results, the LSTM model outperforms the ARIMA model with respect to accuracy in a dataset of 60 data points (RMSE 0.037618). The situation changes, however, when they look at a bigger dataset with 228 pieces of data and see that the ARIMA model outperforms the LSTM model in terms of accuracy (RMSE 0.006949 vs. 0.036025). The LSTM model often beats the ARIMA model in missing data settings, although both models' performance drops down as the total amount of missing values increases. In terms of speed, the ARIMA model is light years ahead of the LSTM model.

Using data from 299 individuals suffering from left ventricular systolic dysfunction and class III/IV heart failure, the authors of [22] want to do a comprehensive survival analysis with survival prediction. In a survival analysis, the number of participants who managed to stay alive after a mediation is tracked over time to determine the impact of that mediation. Survival time is defined as the amount of time it takes to get from a certain starting point to an endpoint, such as death, and survival analysis is the study of that time. Cox Potential Hazard regression and Kaplan-Meier estimations were used to conduct the study. KM plots displayed the estimated survival rates vs each clinical trait, as well as the impact of each feature at different levels on survival over time. The study's clinical characteristics were utilized to estimate the hazard of mortality event using Cox regression. Time, age, ejection fraction, and serum creatinine were shown to be substantial risk factors for advanced heart failure based on the research. The likelihood of survival decreases with age and increases in serum creatinine levels. The likelihood of a fatal incident decreasing by around 5.2% is directly correlated with the EF level, which has a positive impact on survival. Early postdiagnosis days have a higher death rate, but once a specific amount of time has passed, the risk begins to decline. Additional risk factors include hypertension and anemia.

Researchers in [23] conducted multi-step-ahead predictions of network bandwidth use using statistical techniques, such as auto-regressive integrated moving average, and machine learning algorithms, such as multi-layer perceptron as well as short-term memory. In order to anticipate the network's bandwidth, use one, two, and three hours in the future, they suggest comparing several methods, including recursive, regulate, multiple-in multiple-out, or variants on these themes. According to

the results, MIMO was superior for forecasts two and three hours in advance, whereas the direct method was superior for predictions one hour in advance. Additionally, the multi-stage methods were beneficial to all three prediction algorithms. They emphasize the significance of their findings for telecom network long-term forecasts.

The forecasting of time series of total everyday solar energy output has been investigated by the researchers of [24] using approaches based on machine learning. Prior to comparing its performance to two other common machine learning techniques, support vector machine, while artificial neural network, the time series is first modeled using the seasonal variant of the well-known classical approach auto regressive integrating moving average. The impressive results achieved by SVM showcase the promise of machine learning-based approaches in that field. Nevertheless, in order to have a better understanding, they need to investigate the causes of ANN's poor yield. Although SVM has shown some success in predicting solar production, there is still room for improvement in terms of overall accuracy. Future research should focus on finding ways to do that.

A technique for predicting when flights would take off using deep learning was suggested in [25]. The first section of that study is an analysis of the variables that affect flight departure time as well as what those factors are. Second, the article builds a GRU model, analyses how various hyperparameters affect network performance, and uses parameter tweaking to find the best hyperparameter combination. Lastly, ZSNJ's actual flight data is used for model verification and comparison analysis. The established model has the following evaluation values: an RMSE of0.42, a MAPE of6.07, and an MAE of 0.3. The model presented in that research reduces RMSE by 16%, MAPE by 34%, and MAE by 86% when compared to existing delay prediction models. Due to the model's excellent forecast accuracy, airport scheduling with collaborative decision-making may be implemented with confidence. Table 1 shows the cons and pros of the model,

Table 1: Comparison analysis models

Model	Cons	Pros
Reference [19]	Very attuned to extreme cases. Firm presumptions.	Competence in managing various time series elements and characteristics. Excellent comprehensibility.
Reference [20]	Very attuned to extreme cases. Compact intervals of certainty.	Aptitude for dealing with level, trend, along with seasonality components that are changeable. Optimization via automation.
Reference [21]	Further information is needed. Rigid guidelines and presumptions. Not easily automatable.	Excellent comprehensibility. Is confidence interval realistic? Objective predictions.
Reference [22]	The holdout error is higher. Extended periods of instruction and assessment.	Excellent comprehensibility. Clearer than competing models. Handles unknowns with ease. Manage the component variance.
Reference [23]	Not really easy to understand. Creating confidence intervals for the predictions is a challenging task. Further information is needed.	Minimal presumptions and constraints. Capability to manage intricate nonlinear situations. Extremely accurate forecasting capabilities. Is amenable to automation.
Reference [24]	- The weight initiation is a determining factor. -Problems with hardware reliance, overfitting, and generalizability - An issue with local minima	It is more generic and versatile, can handle numerous input variables, supports multivariate inputs, has excellent results for nonlinear time series, and can properly map input and output connections. It may not need a scaled or stationary time series as an input.
Reference [25]	- Strictly limited in its ability to handle real-world issues - I am unable to manage corrupt or missing files.	Makes use of lag and shift in previous data "Increase precision" with the use of a regression model and a moving average

3 Methodology

A. Event sequence dynamics

A knowledge graph that describes events, event classes, as well as event (class) interactions using "events" as its unit of knowledge. In addition, the event knowledge graph represents the norms and trends of event occurrence or progression via a series of scenario models. All of this information forms the basis of our suggested strategy for predicting future events. To ensure that this work is comprehensive, this part provides the necessary concepts of an occurrence knowledge graph and describes the event prediction.

Event knowledge graph model

The event knowledge graph depicts a scenario in which an event takes place at a given instant in time inside a certain setting, with several actors and displaying distinct action traits and state transitions. To define an event in the event knowledge network, we refer to the definition in.

$$E::=\langle \Lambda, P, O, L, T\rangle \quad (1)$$

The five components that make up an event are the building blocks of knowledge. The event's collection of activities is denoted by A. P stands for the set of people who took part in the event. O is the collection of things that are carriers of the event. The event takes place at venue L. Time, denoted as T, is the duration of the event. Among the elemental connections that may be found between events and their elements are has Participant, hasObject, hasAction, hasLocation, and hasTime.

With an event ontology and many event instances, the event knowledge graph is a knowledge base that is constructed around events and designed for various application domains. Here is a description of what it means.

$$EKG::=\langle EOs, EIs\rangle \quad (2)$$

EOs stand for the event ontology, whereas EIs stand for the event instance library. Concepts of event classes, connections between event classes, and rules for assertion and inference about event classes make up the event ontology. This is the best way to explain what the event ontology is.

$$|\ EOs::=\langle ECs, Event\ -\ Relations, Rules\rangle \quad (3)$$

ECs stand for the collection of event types. A taxonomic relation (is _ a) while logical relations (such as causal, isComposedOf, follow, while concurrence) are all part of the collection of event class relations that are represented by Event _ Relations. Rules are a set of inference rules that may be used to construct different types of reasoning for event classes. Among the models included in the event ontology are those representing event hierarchies and event scenarios. Connecting the various event types via logical relationships creates the event scenario model. Aside from that, it mirrors the pattern of the happening of a first occurrence and a series of following events that are put in motion by it. A taxonomy connection and event classes make up the event hierarchy model.

Numerous event instances, described as follows, are housed in the event instance library.

$$Els::=\langle Events, Event\ -\ Relations\rangle \quad (4)$$

in which the collection of event occurrences is represented by Events and the relations between those instances are represented by Event _ Relations. A particular event is represented by an event instance, which is a concrete implementation of the idea of an event class. It is usual practice to get event instances from databases or text. The inherent logic and evolutionary trends between events are expressed by the identical logical relations among event instances as among event classes.

It is our hope that the computer, given the present situation, can comprehend "what happened" and provide "what will happen ahead" when it comes to event prediction using event knowledge graphs. Allow me to paint a picture to help clarify. The boy's keen perception alerts them to certain happenings the moment he enters the door to his house. First, his instructor is chatting with his parents; second, his parents' faces reveal their frustration. Maybe the lad has been through this before and knows it's not a good sign; maybe a "storm" is on the horizon. We want to provide robots with this capacity to learn from experiences and respond appropriately. The first occurrence and any potential concurrent events are used to extract the characteristics of the occurrence scenario information, as previously stated. What follows is a more formalized version of the event scenario details:

$$ES = EI_e(A_e, O_e, L_e, T_e, P_e) + \sum_n EI_{ec}(A_{ec}, O_{ec}, L_{ec}, T_{ec}, P_{ec}) \quad (5)$$

EI_c signifies the first event e that contains the argument data, while EI_c stands for the data associated with the event ec that occurs concurrently with e. ES represents the scenario information's feature vector. We represented the goal of predicting the occurrence of an event using scene data as a multilabel classification problem. In order to determine the likelihood of each event type, we developed prediction algorithms to analyze the scenario data. To get the result vector, we first projected the scenario data into several result spaces using a linear function. The next step

was to create an analytical function that would take the result vector and return the occurrence probabilities of each event type.

$$W_R = \text{Linear}(ES_e) \quad (6)$$

$$P(\ell) = \text{Sigmoid}\big(\log_\ \text{soft}_{\max}(W_R)\big) \quad (7)$$

The global fluctuations in the multivariate events sequence are conditionally homogenous given the history, and this may be expressed by a probabilistic parameterization of an ordered procedure over labels in L $\Theta = \{\Theta_X : X \in \mathcal{L}\}, \Theta_X = \{\theta_{x|h}\}$ s.t. $\sum_{X\in\mathcal{L}} \theta_{x|h} = 1$ for every distinct history h, where $\theta_{x|h}$ denotes the likelihood of occurrence label X happening at any point in the given history's sequence. With just a portion of the event labels' dynamics taken into account $\mathbf{X} \subseteq \mathcal{L}$, Assuming that the set L\X is not empty, we create a matching random variable X that has one state for every tag in X and one state for if the label belongs to L\X. If X is a complete subset of all labels, then ($\mathbf{X} \subset \mathcal{L}$), there are $|\mathbf{X}| + 1$ states of X; we denote these as x. We use $\tilde{\Theta}_{\mathbf{X}}$ to represent the total of all possible outcomes across all labels $\mathbf{X} \subseteq \mathcal{L}$, i.e. $\tilde{\Theta}_{\mathbf{X}} = \{\tilde{\theta}_{x|h}\}$ where $\tilde{\theta}_{x|h} = \sum_{X\in\mathbf{X}} \theta_{x|h}$, which is given in Fig 1.

(i). Missing data imputation

We provide an ensemble approach to the missing data issue in time series forecasting by combining two forecasting models with advantageous diversity—that is, models that function on various time series dynamics—into a single model. Time series values may be related to earlier time series values due to a certain dynamic that controls the forward flow of information. Time series values may also be stated in terms of future values thanks to the backward dynamic. Since the two dynamics are distinct, they will provide the ensemble with variety. Take the interval from t=M + 1 to t=M +J and assume it is absent from the time series.

We take into account the forward-looking model that estimates the missing variable at time t by predicting it using the lagged prior values.

$$t = M + 1 \quad (8)$$

we use xM−L−1, ..., x ˙ M as a parameter for our model. In addition, we create a "backcaster" model for backward forecasting that uses future values of the time series to predict missing values; for example, if we want to estimate the missing value at epoch t=M+J, we may utilize the following inputs: xM+J+1,..., x ˙ M+J+L. The next step is to put up an ensemble that includes both the forecaster as well as the back caster. To be sure, this is just the beginning. After the missing values have been estimated for the time series, we combine the initial training patterns with the new ones to form an augmented training set. To get stronger models, we retrain the forward and backcasting systems using this more comprehensive training data. This cycle of iterative improvement continues until the additional benefit is no longer noticeable.

B. Markov Models (MMs)

To identify the minimum influencing set, it is sometimes necessary to model the dynamics of a single or small set of labels that are important to the modeler. This is the case in many applications. In the context of knowledge discovery using events sequence datasets, this is very relevant. For every label set X∈L and every SMM function s(·), the unique minimum influencing set exists. Consequently, we provide a set of models that associates the frequency of labels from past events that belong to a subset U with the randomized variable X that corresponds to a label set X L. In order to make a confined history conditionally independent from all other histories given a SMM at any location, we want to allow Memorizing it with regard to these influential labels U for the random variable X. Thus, $P(x \mid h_i) = P\big(x \mid h_i^{\mathrm{U}}\big) = P(x \mid s_{\mathbf{U}})$ where $s_{\mathbf{U}}$ is the SMM state, and for every state x of the X random variable and every location i in an event sequence, which is given in Table 1.

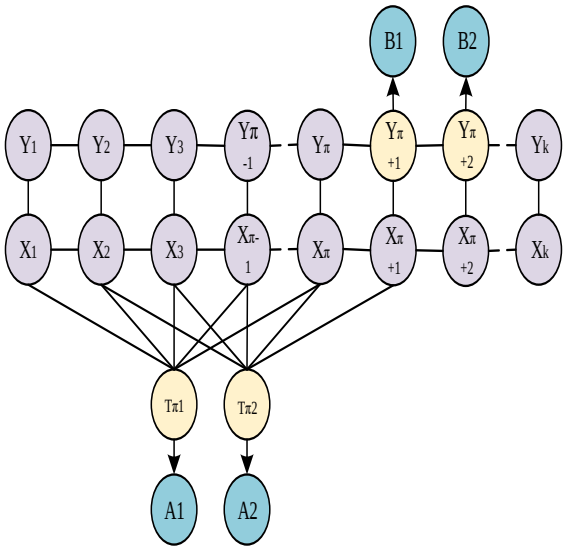


Figure1: Event Analysis using MMsThe time series forecasting technique can ly describe the framework of the variable's sequence without considering other related factors, while the causal prediction technique can only use the causal relationship among a variable along with additional variables.

Neither method can describe the framework of the variable's own time series. A string of variables that are not all known at the outset A set {xN} may be used to represent xN, which is referred to as a random sequence. It is also possible to create a random vector X in a multidimensional random space, with each component denoted by xi. Afterwards, the so-called time sequences are arranged chronologically; that is, the subscript in xi denotes the time variable t, wherein t is an integer representing the growth of the time interval, that is referred to as a random sequence. It is a time series as well. The standard way to express it is with {xt}. Because it is relative to the present instant, the time series' time variable t may take on either a positive or negative integer value. A negative number indicates that its generation occurred before to the present instant, whereas a positive number indicates that its generation occurred subsequent to the current moment. For this reason, in order to put the forward-backward algorithm discussed in this article into practice, one must first train the hidden Markov model's parameters using the definitions provided here. Only then can one determine and foresee the hidden state of the financial time series at different points in time.

Once the hidden state of the series at time 1..., T has been obtained and predicted for time T + 1, the next step is to choose an appropriate technique for forecasting the financial time series. Models based on least squares support vector machines and nonparametric kernel regression continue to form the backbone of this work. Two subsequences, the normal state sequence as well as the abnormal state sequence, were created from the initial financial time series. To get superior prediction results for these two subsequent sequences, it is necessary to pick prediction techniques based on their unique qualities.

Let us assume that the initial network sequence provided consists of a string of observations made at certain times $O = \{(T_i, X_i, Y_i)\}, i = 1,2,\cdots,N$ includes events related to network traffic (where n is the total events). In the initial network traffic sequences, X represents time, Y indicates network events, with nominal, real, and binary values. A regular interval time series data transformation is necessary for identifying the underlying patterns of network activities over time from the time sequence observation series (O). There are three stages to our method: Creating one-hot encoded variables, building time series using pre-defined time scale t_s, and creating forecasting models are the three main tasks. The suggested method was tested using two different time scales (t_s=60 and 120 s) in order to find out how well it worked.

A collection of network traffic series of data in t_s is transformed into time series data by extracting temporal characteristics and translating them to values across time. The first step is to use a pre-established time scale to divide the raw data t_s. The pre-established time scale determines the creation of a new time index t_s over time, $\nabla t_i = (t_s * c) - \nabla t_{i-1}, c = 2,\cdots,t_N, i = 2,\cdots,t_N, \nabla t_1 = t_s$ where $t_N = \frac{m_t}{t_s}$, m_t serves as a cap. This results in the creation of a fresh time index as $\nabla t_i = \{t'_1, t'_2, \cdots, t'_N\}$. Within each time index, ∇t_i comprises a series of tuples $\{(X_i, Y_i)\}$ creating $M \times J$ matrix $\left(X_i \in R^{M\times f}\right)$ and $M \times D$ matrix $(Y_i \in R^{M\times D})$, where $M(M \geq 1)$ shows how many observations there were at time ∇t_i, where J is the total amount of variables and D($D \geq 1$) is the size of the dependent variables. The size of M may change over time due to variations in the amount of network events. The number of network events per second for the dependent variables that are one-hot encoded across ∇t_i is computed as $C\left(Y_i^k\right) = \Sigma_1^{n_t} I_{Y_t}(\delta_i)$, If every network event is considered normal or an attack, it is indicated by δ_i. In addition, for the nominal variables, we quantify the frequency of every one-hot encoded variable across ∇t_i. For example, the count of utilized port numbers over ∇t_i is taken into consideration for the variables (source along with destination port numbers). In order to provide time-series information with similar intervals for the other factors, an appropriate value is measured for every M-dimensional vector across ∇t_i. We provide a technique in this work that converts values from the initial time sequences into time series elements by use of the wavelet transform with permutation entropy. Using both methods (DWT and PE) have many benefits, such as being able to spot unexpected changes in network events and showing how behaviors of these events have changed over time. Network traffic and other non-stationary data types are good candidates for DWT's

temporal and frequency domain analyses. It does this by repeatedly splitting the data into its component bands. That is, data is passed through highpass and lowpass filters in a preset order to create approximation and detail coefficients. At each level of decomposition, the coefficients reflect the time and frequency data by which the level is informed.

$$w_\varepsilon = \langle d(t), \phi_{(r,r)} \rangle = \int_{-\infty}^{\infty} d(t)\phi_{(r,r)}dt \quad (9)$$

where $d(t)$ shows data, $\phi_{(\tau,\gamma)}(t)$ stands for a mother wavelet function, whereas τ describes the frequency resolution (also known as scale) and γ stands for the shift parameters. Rounded estimate values $(a_{(\tau,\gamma)})$ display data at low frequencies, but the precise coefficients ($d_{(\tau,\gamma)}$) display the metrics that are very relevant to the data. The wavelet coefficients are analyzed using PE. It combines entropy with symbolic patterns to provide a measure of complexity. The coefficients were specifically used $a_{(\tau,\gamma)}, d_{(\tau,\gamma)}$, and $a_{(\tau,\gamma)} + d_{(\tau,\gamma)}$ characteristics to be extracted. The purpose of PE is to build subsequences (s_i) with an embedding dimension (e_d) that has already been established. After that, in order to get the order, every subsequence is transformed into a different permutation $\pi(i) = \{0,1,\cdots,e_d\}$. We can calculate the permutation's probability distribution as $p_{\pi(i)} = \frac{\delta_{\pi(i)}}{|x_i|}$, where $\delta_{\pi(i)}$ displays the pattern $\pi(i)$ as it occurs. In conclusion. To get the permutation entropy, we use Shannon's rule as $\Sigma_f - p_{\pi(f)} \times \log\left(p_{\pi(f)}\right)$.

In addition, statistical feature ($\mathcal{P}$) is removed as $\chi(w_{q_1}, o_i)$, where $\chi(\cdot)$ designates the ANOVA test, w_{q_1} signifies the thorough coefficients of o_i, also o_i symbolizes the i-th vector of the initial sequences O at ∇t_i. If the original sequences with the wavelet coefficients vary statistically in any way, this characteristic will indicate it as a p-value. In addition, we use the initial moment to calculate an extra feature $(\mathcal{E})$ as $\frac{1}{|a_i|}\sum o_i$ in ∇t_i. Method 1 introduces a pseudo-code that normalizes a time series of network data to a specified interval (t_s).

C. Feature selection

When working with a target variable, feature selection involves picking out the discriminative attributes that have the most impact. By eliminating features that do not contribute to the identification of the target variable, the goal of feature selection is to lower the computational cost of the model.

PCA and p-value-based filtering for event sequence prediction

The size of the feature space, which includes things like the number of event kinds or time intervals, may be reduced using principal component analysis in event sequence prediction. This may be particularly helpful when working with intricate event sequences including a wide variety of event kinds or when working with very fine-grained time intervals. When using p-value filtering, features are chosen according to how well they statistically predict the target variable, which is the event sequence in our example. Finding out which traits are most tightly linked to the event sequence while other ones are less important is aided by this. When using p-value filtering, features are chosen according to how well they statistically predict the target variable, which is the event sequence in our example. Finding out which traits are most tightly linked to the event sequence while other ones are less important is aided by this. The p-value of each attribute is found by running a statistical test on it, such as a t-test or a chi-square test. If the characteristic didn't significantly impact the event sequence, then the p-value indicates the likelihood of seeing the given outcome (or an even more extreme result). If the p-value is little, below a certain threshold (e.g., 0.05), then the characteristic is statistically significant along with can be valuable for making predictions. If you want to know what kinds of events or patterns of occurrences are most likely to happen in a given event or sequence, you may use p-value filtering in event sequence prediction. We suggest PCA as a viable option for reducing the temporal dimensionality of duplicated time series and identifying important characteristics. Particularly, PCA reduces the likelihood of overfitting in deep-learning algorithms by eliminating redundant and irrelevant variables and by decreasing correlations across various time steps. Additionally, PCA maps time series data onto principle components that reflect similar characteristics by examining the complete training dataset. This allows it to identify shared patterns. While reducing the length of the original series, this method maintains important statistical details. To reduce computing demands, time series may be preprocessed using PCA prior to being fed into deep-learning models. Feature space dimensionality reduction is possible using PCA. To extract the most useful information from the condensed set of characteristics, p-value filtering may be used. The accuracy of predictions and the interpretability of models may both be enhanced by combining these two factors. With its many benefits, principal component analysis (PCA) is a powerful tool for reducing time series data.

By removing characteristics with low variance and keeping those with large variance, it is a powerful technique for noise reduction. The essential statistical properties of the initial series are also preserved by PCA.

PCA is a powerful method for reducing noise in time series. Using a fresh collection of orthogonal components, PCA successfully removes the noise from the lower variance components while keeping the original historical series' main information. By re-creating the initial time series using the principal components, PCA-inverse transforms make this noise reduction visually apparent.

For this study, we analyzed the input-output connection using p-value and correlation metrics. As an indicator of how likely it is that an observation will be made, we have the p-value. The hypothesis is either accepted or rejected based on this likelihood. The following is the procedure for calculating the p-value using Equation (7):

$$z = \frac{\hat{P} - P0}{\sqrt{\frac{P0(1-P0)}{n}}} \quad (10)$$

Here, the sample size is denoted by n, the presumed population under the null hypothesis is denoted by P0, and the sample percentage is denoted by $\hat{P}$. Then, using the z-value as a starting point, we can calculate the p-value. Since the p-value did not provide the desired outcomes, we resorted to correlation metrics in our feature selection process.

A statistical tool for determining the degree of association between two variables by comparing their relative moments is the correlation coefficient. There is a range of +1 to -1 for its value. A very positive relationship among two variables is shown by a correlation coefficient value of +1, whereas an extremely negative association is represented by a value of -1. A correlation coefficient of 0 indicates that the two variables are unrelated.

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \quad (11)$$

In Equation (4), x_i the sample's X variable values, with $\bar{x}$ being the mean of the X variable; the sample's Y variable values, with $\bar{y}$ being the mean of the Y variable.

Algorithm 1: PCA	
a.	Locate the data set's midpoint.
b.	Do the square correlation calculation (c) in $N \times N$.
c.	The eigenvalues and eigenvectors of the covariance matrix can be calculated.
d.	Find the initial element by selecting the matrix's biggest eigenvector c
e.	Find the second part by selecting the eigenvector that is the next biggest in the matrix **c**.
f.	Create a new $N \times M$ matrices in the features the domain, where M is the desired number of elements.

Two key points are to be kept in mind when working with PCA, though: first, the second element of PCA should be orthogonal to the first component. PCA doesn't change the number of samples, but it can change the value of the samples to highlight the differences between datasets. For instance, let's say that a Markov chain describes the existence of certain irregularities in ℓ items coming in at a store, and that the first item in it undergoes an examination of these irregularities to determine its state (when that passes through the queue). By following the queue rule and counting the items as it exits the queue, we have information "with anticipation" on the state of the ℓ-th item. This example shows that observation with the excitement does not always require future occurrence prediction.

4. Results & discussion

We evaluate our learning technique and two proposed MMs in the following trials. Our research is based on actual occurrences and event sequences taken from actual texts, numerous event sequence datasets found in books and musical compositions. We test Python's learning capabilities using fake data in an experiment. In this study, we examine the dynamics of a basic event sequence MMs across five event labels, with the one label of interest having two additional labels as its minimum influencing set. As a function of the number of sequences (K) created, Table 1 illustrates the mean F1 scores comparing the estimated and ground truth influences over several generated sequence datasets. As the tendency continues to rise, it will inevitably converge.

A. Implementation details

All of the necessary libraries were utilized during the implementation in Python 3.9. These included PyTorch 1.11.0 for DGNN model building and training, NumPy 1.21.0 and pandas 1.3.3 for numerical operations and information handling, tqdm 4.62.3 for progress visualization, DyGLib for DGNN executions while link prediction components, and Matplotlib 3.4.3 for result visualization. The server used for all the trials had the following specs: Ubuntu 20.04 OS, 256 GB RAM, 2 TB NVMe SSD, 32 GB VRAM, Intel Xeon Gold 6230 CPU (2.10 GHz), and NVIDIA Tesla V100 GPU.

A 200-unit batch size, two attention heads, a learning rate of 0.0001, ten iterations, a 100-unit time

embedding dimension, a 0.1-unit dropout rate, and a 15% validation/test set ratio were all part of the conventional experimental configuration. To guarantee temporal relevance, historical neighbors were selected using the "recent" technique, whereas negative edge sampling applied a "random" strategy. The settings supplied by DyGLib were used to optimize parameters for each DGNN model, including the total amount of neighbors and layers.

Multivariate time series information with periodic patterns are the target of our model. When identifying periodic events is crucial, like in link forecasting event detection, as well as temporal connection analysis, it works very well. Having said that, the model is subject to the following restrictions and limitations. Input data for the model should have aspects of time, nodes, and edges. It works well with datasets characterized by a high degree of periodicity. Datasets that are neither periodic or irregular could lead to worse performance. The available computing resources determine the model's scalability. By applying an NVIDIA Tesla V100 GPU, we ran our tests on datasets that included up to 33 nodes with 175,360 edges. Memory and processing power may need to be increased for datasets that are larger. Issues with periodic patterns and temporal dynamics are well-suited to the approach. Different methods could work better with static data or graph issues that aren't time-dependent.

B. Dataset

Using the five real-world datasets, we do experiments. At the 0.8 mark on the time line, we divide the train/test set in half, with the segments to the left being utilized for training with the segments to the right for testing. We further divide 10% of the train set into a validation set to prevent overfitting. Starting using a rate of learning of 0.001 and decreasing it by roughly a factor of 10 every 20 iterations, we train the models we create for 100 iterations on a single GPU and a batch size of 1000. There are two sources of this enhancement. To begin, the Markov model is a powerful tool for decomposing time series into their component hidden states; second, the subsequence of the decomposed normal state mitigates the impact of outliers. Second, the model's prediction error is effectively reduced by the process of conversion hybrid prediction model.

B. Datasets

We take into account the following organized datasets, some of which are extracted from event datasets with time stamps that are disregarded (thought to be inaccurate or absent).

In our studies, we use five real-world datasets. Two of them are publicly available ones (DJIA30 as well as WebTraffic) from Kaggle1. The other three are obtained from China Telecom2 (NetFlow), State Grid3 (ClockErr), and Alibaba Cloud4 (AbServe). The statistics for the whole dataset are shown in Table 1.

- **Web Traffic Time Series Forecasting (WebTraffic) -** We find this dataset on Kaggle. It keeps track of the number of views for a particular Wikipedia page and includes around 3 million daily reads. The goal is to use the most current data from the last 12 months to forecast if there will be a significant increase (curve slope > 1.0) in the next 30 days. We find around 2 million false positives and 900,000 positives (rapid increase).
- **DJIA 30 Stock Time Series (DJIA30) -** We find this dataset on Kaggle. Every one of its fifteen thousand daily readings documents four observations made throughout a trading day: three types of trade prices and a trade number. The objective is to use the most up-to-date data from the last year (50 weeks) to forecast five trading days with abnormally volatile prices (variance more than 1.0). Approximately 12,000 typical examples and 3,000 outliers are found by us.
- **Information Networks Supervision (NetFlow) -** China Telecom is the source of this dataset. Each of the approximately 238K measurements documents the incoming and outgoing data from a network equipment on an hourly basis. The gadget will record an alert if it detects an anomalous flow via its ports. Based on information from the last 15 days, our objective is to forecast future anomalies (next day). We find around 200,000 typical examples and 20,000 outliers in total.
- **Abnormal Server Response (AbServe) -** Alibaba Cloud has made this dataset available. The system is comprised of over 12,000 server monitoring series, with each series recording the minute-to-minute readings of various metrics such as CPU, disk, memory, and more. An anomaly will be recorded in the log if a server doesn't reply. Our objective is to use the data from the last hour to forecast outliers within the next five minutes. We find 11.8K typical examples and 0.2K outliers overall.
- **Watt-hour Meter Clock Error (ClockErr) -** The Chinese State Grid was kind enough to provide this dataset. The data is comprised of around 6 million measurements taken weekly, with each reading documenting the watt-hour meters' deviation time and delay. The meter is considered to be malfunctioning if the deviation time is more than 120. We aim to forecast next month's anomalies using data from the previous 12 months. We find around 5 million typical examples and 1 million outliers altogether.

We emphasize that the selected event sequence dataset determines the learned MMs. Every single influencer in these case studies was trained using very little domain-specific data. In order to successfully implement the models in reality, this must be remembered at all times throughout the analysis. We verified the model's prediction accuracy, as illustrated in Figure 2, to assess its reliability. We calculated the model's overall prediction accuracy by averaging the final accuracies after finding the accuracy for each scenario independently. Each case had a sequence randomly eliminated during testing. In order to fit the model, the remaining sequences were used. Once the fitting was finished, the model used the deleted sequence's beginning sequence to forecast the next two steps. The model had a 90% success rate in predicting one of the phases, according to the findings. The model consistently properly predicted the following two steps in every single example. A whopping 96.7% of the time, the model gets the predictions right. Because it drastically reduces the amount of useable data, missing information in time series is a major hurdle to the effective operation of forecasting models. To estimate the missing values of a time series, we provide a paradigm similar to multiple imputation. The foundation of this framework is the construction of ensembles of predictions that are iterative and subsequent, with the goal of filling in the missing data. The algorithm's iterative nature enables the prediction accuracy to be improved over time. Furthermore, the ensemble benefits from the time series' diverse forward and backward dynamics. The created framework is versatile enough to use any underlying model for traditional or machine learning forecasting. Using both linear and nonlinear underlying forecasting algorithms, we successfully evaluated the suggested technique on large data sets.

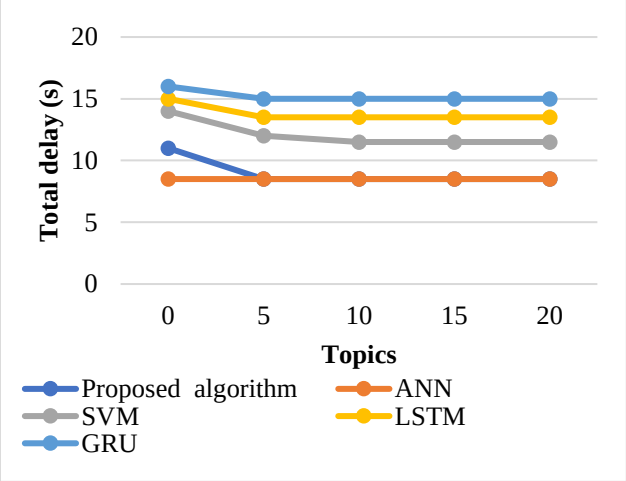


Figure 2: Total delay

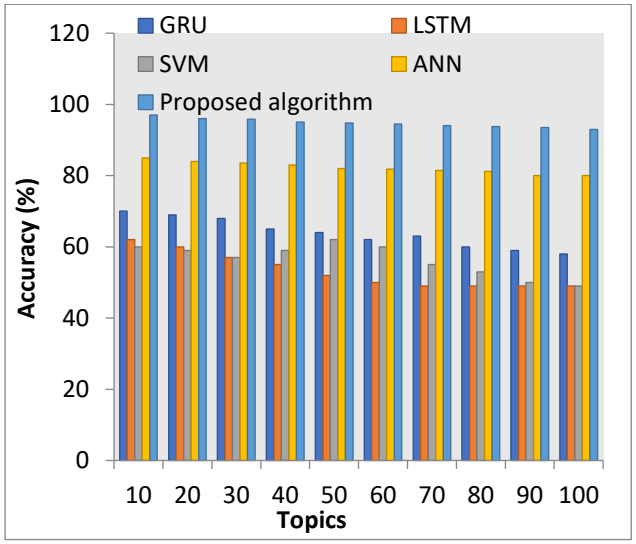


Figure 3: Accuracy analysis

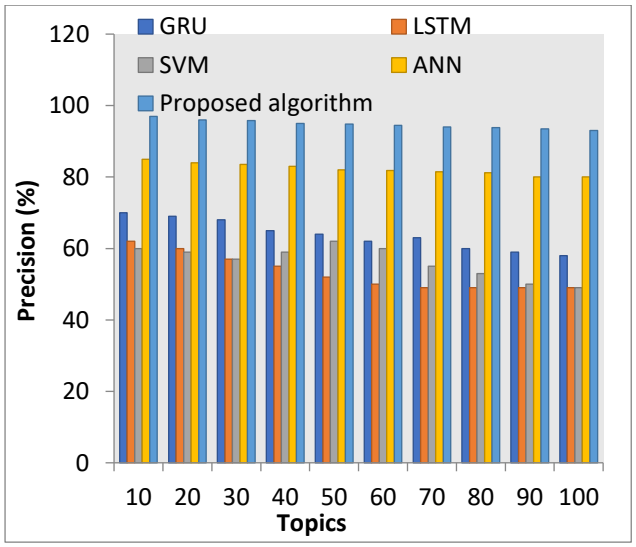


Figure 4: Precision analysis

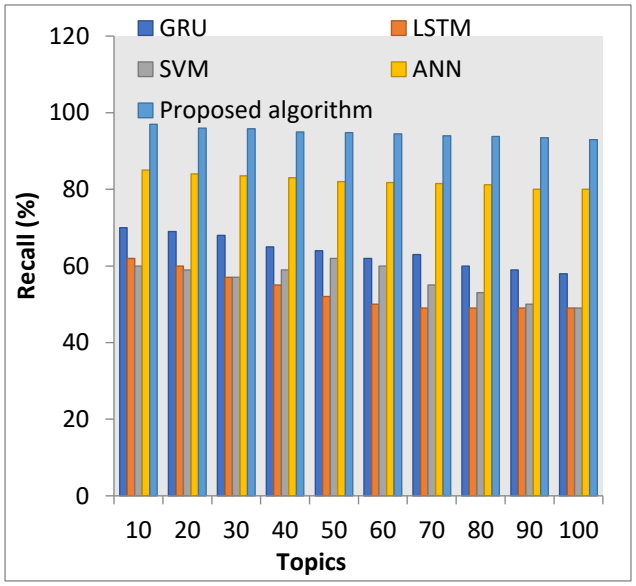


Figure 5: Recall analysis

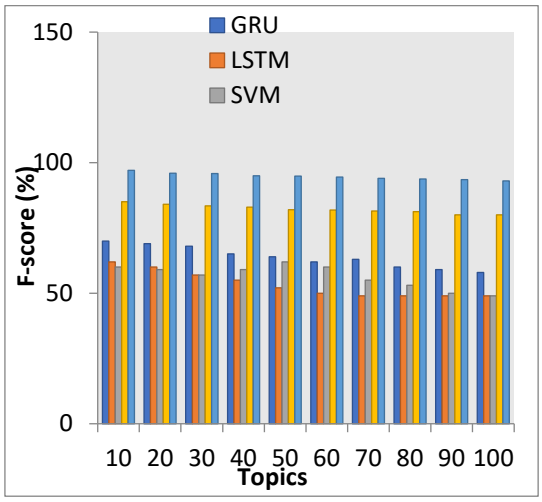


Figure 6: F-score analysis

Table 2: Prediction analysis

Scenario	Overall Prediction Accuracy
Topic 1	91.25%
Topic 2	92.15%
Topic 3	93.14%
Topic 4	94.14%
Topic 5	91.25%
Topic 6	93.14%
Topic 7	94.75%
Topic 8	94.15%

Fig 4, 5, and 6 shows the precision, recall and f-score for precision, recall and f-score, respectively. Table 2 illustrates the overall prediction accuracy for different topics using markov models.

Ablation Study

Here, we establish ablation experiments to examine how various event representations impact the outcomes of the predictions. Eliminating arguments and relations from the event graph was part of this process. Experiments with relation-level ablation preserved just the arguments while removing the edges of concurrent event relations from the graph. While keeping the graph structure and other characteristics, the argument-level ablation tests eliminated the events' spatial and temporal dimensions. You can see the outcomes of the ablation tests in Table 3.

Table 3: Comparisons with standards and ablation trials

Model	Accurate Matching	Recall	Precision	F1-Score
[19]	87.13	91.97	86.87	89.03
[22]	88.76	87.78	89.06	87.07
[20]	89.79	88.85	84.96	88.12
[23]	83.94	86.85	89.08	86.97
[24]	87.15	89.97	89.82	86.05
[25]	84.84	86.32	86.88	85.88
Proposed model	96.86	98	94	92.56

Various ablation tests showed that the model's performance dropped somewhat, as can be observed in the results of the experiment. Recall values increased more noticeably in the relation-level ablation trials, suggesting that although concurrent event inclusion did enhance accuracy in forecasting, it was also a major contributor to the model's more cautious forecasts. Reducing metrics in the argument-level ablation trials demonstrated that geographical and temporal information improved performance on the event prediction test. To test the efficacy of the event prediction model we presented in this paper—one that relies on event knowledge graphs—we built an event knowledge graph by hand in the transportation sector. We investigated the potential of a model-based graph attention neural network to validate the utility of a heterogeneous graph transformer for occurrence scenario characterisation, with the aim of better integrating the data contained in various arguments and concurrent events. The significance of spatial and temporal aspects in event representation was also confirmed by our tests.

More prediction approaches will be investigated and the possibility of building more complicated event linkages will be considered in future investigations. There are several sorts of entities represented by event arguments. To further enhance the forecast, it may be helpful to consider the impact of various entity kinds on the model. We will think about adding multimodal data to the event knowledge graph enabling real-time monitoring of unexpected occurrences and quick decision-making in the future. We are thinking about adding IoT to get additional data for decision-making, which will make the model better at making decisions.

5 Conclusion

For dynamics in a sequential event dataset, we have suggested summary Markov models. Two of these models use different summary mappings to determine which event labels are influential. We demonstrate the robustness of our models compared to previous techniques via experiments on structured datasets and event sequences derived from text. The suggested model's key benefit is that they find influencing sets and achieve prediction performance that is on par with baselines. By combining parameter sharing concepts from variable order Markov models with other methods for summary mapping, including counting-based models, and by adjusting the size of the summary range for expressive models, the scope of summary Markov models might be enlarged. An obstacle for future research is the management of noisy event sequence datasets including many event labels that are not meaningful. This work presents a one-step approach for predicting the subsequent hidden state of a time sequence when the sequence comprises two kinds of hidden states, based on the premise that the hidden Markov model's hidden state is a first-order Markov process. This research suggests using several models to forecast the concealed state's value based on varied amounts of time series sample information after obtaining the prediction result.

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Topology-Aware, Performance-Driven Adaptive Routing in Software-Defined Networks Using Dual-Agent Reinforcement Learning

Deepthi Goteti[1*], Vurrury Krishna Reddy[2]
[1,2]Department of Computer Science & Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India-522302
E-mail: 2102031088@ kluniversity.in, vkrishnareddy@kluniversity.in
[*]Corresponding author

Keywords: Software Defined Networking (SDN), Reinforcement Learning, Policy-Gradient, Routing Optimization, R-Learner, R-Optimizer, QoS, Dijkstra Baseline, Network Topologies (Fat Tree, Abilene, Custom, Dense Mesh)

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This research explores adaptive routing in Software-Defined Networks (SDNs) using reinforcement learning. Two models—R-Learner (Q-learning) and R-Optimizer (policy-gradient)—are evaluated against the Dijkstra baseline across four topologies: Fat Tree, Abilene, Custom, and Dense Adaptive Mesh. Experiments run over 100 TCP/UDP traffic episodes using Mininet and the Ryu controller. Key metrics include throughput, jitter, round-trip time (RTT), and packet loss ratio (PLR). Statistically validated results show R-Optimizer outperforms R-Learner, achieving ~7.4% higher throughput, 44% lower jitter, 19.5% lower RTT, and >50% lower packet loss. Both models also surpass Dijkstra in throughput and delay reduction. These results support reinforcement learning as a viable approach for real-time SDN routing and future controller integration.

Povzetek: Članek predstavi dvofazni model za adaptivno usmerjanje v SDN s Q-learningom (R-Learner) in policy-gradient pristopom (R-Optimizer). Preizkusi v Mininetu na štirih topologijah pokažejo, da R-Optimizer izboljša prepustnost (~7,4 %) in izgubo paketov (>50 %) ter občutno prekaša Dijkstrov algoritem.

1 Introduction

The rapid demand for data-driven services, cloud platforms, and real-time applications has made network environments more complex and more challenging to manage. These conditions often overwhelm traditional routing methods. In response, researchers have turned to reinforcement learning (RL) as a tool within Software-Defined Networking (SDN) to support more adaptive, policy-based routing that can adjust to changing network demands [1]. Traditional network infrastructures, which rely on fixed, distributed routing setups, may frequently fall short of delivering the speed and flexibility when needed to maintain consistent Quality of Service (QoS) [2]. SDN helps overcome these issues by separating the control and data planes, allowing for centralized control and flexible, real-time reconfiguration [3].

The SDN architecture comprises an application, control, and data plane interconnected via protocols like OpenFlow to support real-time management and policy enforcement [4]. Figure 1 illustrates the Architecture of the SDN system with integrated reinforcement learning. The R-Learner and R-Optimizer (RL Agent) reside in the Application Plane and interact with the SDN Control Software in the Control Layer via APIs to install routing decisions dynamically.

The Control Layer communicates with the network infrastructure using OpenFlow to manage network devices and enforce routing policies. The design maintains the traditional three SDN planes: the Application Plane, where the R-Learner and R-Optimizer agents calculate routing decisions by exploring path diversity under dynamic traffic patterns. The Control Plane is managed by the Ryu controller and extended with a custom module to enable the RL agents to install or update flow rules dynamically.

The Data Plane consists of OpenFlow switches that forward traffic based on the flow rules set by the controller. The RL agents monitor network statistics like link utilization and RTT through the southbound interface, select optimal routes, and then guide the controller to modify flow tables in real time. This separation of roles—keeping the learning logic in the application plane and the rule enforcement in the control and data planes—ensures greater modularity, makes the system easier to debug and allows for the easy integration of new learning strategies without changing the switch infrastructure. Learning effective routing policies has become critical as modern networks demand millisecond-level responsiveness and context-aware decision-making. This way drives the exploration of intelligent methods beyond traditional static or rule-based strategies.

While SDN significantly improves control capabilities,

real-time route optimization remains challenging [5]. Classical routing algorithms such as Dijkstra's and Equal-Cost Multi-Path (ECMP) often respond reactively to network changes and fail to adapt efficiently to link failures, congestion, or topological variation [6][45].

Khan et al. [7] Tested the performance of POX and RYU controllers using Dijkstra-based routing in SDN environments, demonstrating that RYU consistently provided lower latency and higher throughput under varying traffic loads compared to POX. The study emphasized that RYU's modularity and scalability make it better suited for implementing advanced routing strategies, including reinforcement learning while retaining Dijkstra as a comparative baseline for deterministic routing performance under static conditions.

Kumar and Thakur [8] Evaluated Ryu controller performance over Dijkstra, Bellman-Ford, and Floyd-Warshall algorithms using the RYU controller in SDN testbeds. Their findings showed that Dijkstra achieves lower RTT in stable topologies but struggles under dynamic traffic due to its static path selection, leading to congestion and packet drops. This showcased approaches in SDN and the need for adaptive, learning-based routing to address traffic variability and topological changes efficiently.

Naimullah et al. [9] analyzed the performance of POX and RYU controllers using Dijkstra's algorithm in SDN environments and reported that RYU outperformed POX in scalability and efficiency across larger topologies. However, the study also noted that Dijkstra's routing lacked adaptability under congestion, where link failures occur at certain times, also demanding the limitations of classical shortest-path approaches in dynamic SDNs and motivating the exploration of reinforcement learning for more responsive and robust routing strategies.

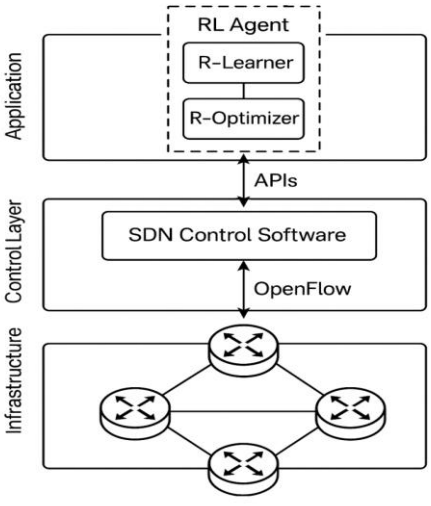


Figure 1: Architecture of SDN with reinforcement learning integration for dynamic routing

As an alternative, reinforcement learning (RL) offers the ability to learn adaptive routing policies by interacting with the environment and optimizing behavior based on cumulative rewards [10]. In recent years, researchers have integrated Artificial Intelligence (AI), particularly reinforcement learning, into SDN controllers to enhance proactive decision-making and traffic engineering [11], [12]. Deep reinforcement learning (DRL) models have shown impressive results in reducing packet loss, minimizing delays, also dynamically balancing traffic loads [13], [14]. Researchers have successfully deployed Graph Neural Networks (GNNs) and Convolutional Neural Networks (CNNs) beyond DRL to improve fault tolerance, detect anomalies, and enhance routing resilience in SDNs [15], [16].

Unlike previous studies that often evaluate RL models within a single, simplified network structure, this work adopts a topology-aware approach. Research Questions To guide this investigation, the study focuses on the following research questions:

- Can a staged reinforcement learning framework, leveraging an initial exploration phase followed by policy-gradient-based refinement, enhance routing efficiency across diverse software-defined network topologies under dynamic traffic conditions?
- How does the policy-gradient-based R-Optimizer compare with the exploration-phase agent (R-Learner) in terms of convergence speed and Quality of Service metrics—such as throughput, jitter, RTT, and packet loss—under TCP and UDP traffic across diverse network topologies?

To investigate the outlined research questions, this study introduces a dual-agent reinforcement learning framework designed for adaptive routing in software-defined networks (SDNs). The framework deals with two complementary strategies: Q-learning (R-Learner), which focuses on exploring the environment, and policy-gradient methods (R-Optimizer), which refine routing decisions based on observed performance under varying traffic conditions.

The approach is tested on four SDN topologies—Fat Tree, Abilene, Custom, and Dense Adaptive Mesh—to understand how network structure affects convergence rates, routing efficiency, and quality of service. These topologies were chosen specifically to represent a broad range of structural complexity, from the regularity of Fat Tree and Abilene to the irregular, high-density layouts of Custom and Dense Mesh. Such variation allows for a more nuanced evaluation of how well reinforcement learning adapts to different network environments. The broader motivation builds on recent work showing that deep reinforcement learning can offer strong results in SDN routing tasks [18, 20], and reinforces the idea that topology-aware testing is essential for drawing robust conclusions [17, 21].

The experimental environment is built using Mininet, which provides a scalable and flexible testbed [22]. Routing control is managed through the Ryu controller [23], and iPerf is used to generate realistic traffic patterns based on TCP and UDP protocols [24]. To benchmark the performance of the learning framework, a traditional Dijkstra-based routing strategy was implemented on the same setup, providing a clear point of comparison under identical network conditions.

We conduct our experiments in each topology with 100 simulation episodes. Moreover, selected samples were analyzed to evaluate performance across key quality of service metrics: throughput, RTT, jitter, and packet loss ratio (PLR). Results show that the policy-gradient-based R-Optimizer consistently performs better than the Q-learning-based R-Learner, particularly in topologies with higher redundancy and path diversity, such as Fat Tree while maintaining adaptability and stability across different network environments. These findings demonstrate how topological diversity significantly influences routing efficiency and learning behavior within reinforcement learning-based SDN routing.

The remainder of this paper is organized as follows: Section 2 reviews related work. Section 3 presents the proposed system. Section 4 describes the experimental setup. Section 5 details the results and analysis. Section 6 provides QoS comparison and section 7 is discussion. Finally, Section 8 concludes the paper and outlines future work

2 Related work

Software-defined networking (SDN) separates the control and data planes, enabling centralized programmability and abstraction of the underlying infrastructure [25]. The controller acts as the network's "brain," dynamically managing flow rules and routing. Due to its modularity in part design, Ryu stands out among available controllers, offering Python design, OpenFlow compatibility, and suitability for reinforcement learning (RL) integration [26].

Traditional SDN routing methods—like Dijkstra's algorithm and Equal-Cost Multi-Path (ECMP)—perform reliably under stable conditions but lack adaptability to congestion, link failures, and traffic surges [27]. Researchers have proposed reactive traffic-engineering solutions, but these still fail to meet real-time, low-latency demands [28]. Moreover, most traditional approaches do not learn from past network behavior, so they cannot improve or adapt over time. To deal with this, researchers have started using reinforcement learning (RL) and deep RL (DRL) for SDN routing [29], [30].

These models utilize deep Q-networks and policy gradient methods to adjust routing decisions based on real-time network feedback dynamically. The goal is to optimize long-term performance rather than reacting solely to short-term events. Studies show that they can boost throughput, reduce delay, and lower packet loss, even under unpredictable traffic loads [31]. Advanced methods like hierarchical and meta-RL improve how fast they learn and how well they handle different network situations [32], [33].

These models also reduce the need for manual tuning, making the system more autonomous and scalable.

Additionally, RL agents can continually adapt to traffic shifts over time without requiring a restart or reset of the entire network.

Recent approaches also include topology-aware learning where models make use of how the network is structured [33]. This helps to make rorouting decicion by the agent understand the role of links, paths, and node positions. Deep learning methods like transformers and convolutional neural networks (CNNs) have been used for traffic prediction, detecting anomalies, and improving routing during failures [35], [36].

These methods can catch early signs of congestion or link stress and adjust routing before problems get worse. Some setups use supervised learning first to teach the model basic patterns, then switch to reinforcement learning to fine-tune behavior in live scenarios. This shortens training time and improves stability.

Other designs use alert mechanisms or graph-based learning to help the agent focus on the most relevant parts of the network at any moment. This is useful when the network is large and links behave differently depending on traffic. These ideas are still developing but show good results in testbeds.

Mininet and the Ryu controller continue to be the go-to tools for testing this kind of setup [39], [40]. Mininet deals wiht complex topologies without needing physical switches, and Ryu makes it easy to plug in custom logic through its Python API. This allows routing agents to read traffic stats, update flow rules, and learn over time. There are open templates available for things like ECMP and custom controller functions, which help speed up testing and cut setup time [41], [42], [43]. These tools make it easier to repeat experiments and build on other researchers' work.

Despite these advances, a gap remains in frameworks that systematically assess RL-based routing across multiple SDN topologies. This study addresses that gap through a dual-agent architecture—R-Learner and R-Optimizer—evaluated on Fat Tree, Abilene, Custom, and Mesh networks, with a focus on convergence behavior and quality of service performance.

3 Proposed system

This section describes a structured SDN flow control framework that works on a two-stage routing process. The system introduces two coordinated modules—Route-Learner and Route-Optimizer—each responsible for a specific phase. In the first stage, the route learner probes the network to identify available paths and assess real-time network conditions. In the second stage, the Route-Optimizer takes the aid of this information to refine routing decisions, aiming to improve traffic distribution and reduce congestion. Both modules are integrated into the Ryu controller, enabling real-time interaction with the network topology. This setup allows the system to

periodically adjust forwarding rules based on updated path and traffic condition data, ensuring efficient routing even as network demands fluctuate. Our implementation followed a two-phase staged framework. In phase one, the R-Learner operated on the live SDN topology to collect QoS data and estimate routing values using Q-learning.

Table 1: Prior RL-Based SDN routing studies

Study	Method	Topologies	Metrics Evaluated	Key Findings	Identified Gaps
Liu [29]	Deep Q-Network (DQN)	Fat Tree	Throughput, Delay	Improved congestion handling	Single topology, no policy-gradient
Kim et al. [31]	DRL (Actor-Critic)	Custom Mesh	Latency, Packet Loss	Reduced delays and PLR	Limited topology diversity
Suh et al. [11]	DRL for Network Slicing	Data Center	Bandwidth, Delay	Dynamic slicing for QoS	Not focused on routing decisions
Chen et al. [33]	Multi-Agent RL	Custom	Load Balancing	Better fault tolerance	No policy-gradient exploration
Xie et al. [19]	GNN-RL	Mesh	Throughput	Captures topology structure	Limited scalability, single topology
Yang & Li [37]	Deep Reinforcement Learning (DRL)	Data Center SDN	Latency, Reward, Speed	Reduced latency by 6.3%, improved reward convergence	Focus on congestion control, lacks multi-topology routing analysis
Ma et al. [38]	Q-Learning	Generic SDN	Throughput, Delay, Load Balancing	Improved throughput by 30%, reduced delay by 25%	Uses Q-learning only, lacks policy-gradient comparison
Kim et al. [31]	Q-Learning + Policy-Gradient (Dual-Agent)	Fat Tree, Abilene, Custom, Mesh	Throughput, Jitter, RTT, PLR	Consistent QoS improvements across topologies	Multi-topology, staged policy-gradient use

Once exploration was complete, it was halted while the topology remained active. In phase two, the R-Optimizer refined routing decisions on the same topology using the Q-table generated by the R-Learner via a policy-gradient method. This structured approach ensured realistic traffic conditions while leveraging prior exploration.

For comparison, we also implemented Dijkstra's shortest-path algorithm in the Ryu controller and evaluated it under identical TCP and UDP traffic across all topologies. This provided a consistent baseline to measure improvements over the learning-based framework.

3.1 Reinforcement learning integration in SDN

Enhance the Ryu controller with custom RL modules to enable intelligent routing in SDN. When the system receives a packet_in event from the switch, it identifies the source–destination context and evaluates all feasible paths. It then selects a forwarding action based on the chosen agent's strategy—either R-Learner or R-Optimizer. In practice, this selection follows a staged approach: the system first operates with the R-Learner to explore and gather routing knowledge under live network conditions and, after sufficient exploration, transitions to using the R-Optimize**r** on the same active topology to refine routing decisions using the knowledge learned during the R-Learner phase. The system verifies each forwarding action.

Furthermore, it observes outcomes like delivery status, delay, or signs of congestion. We later use this information to improve future routing decisions through gradual adjustments. Updated routing choices are applied immediately by installing new flow rules using OpenFlow 1.0, maintaining smooth and responsive network operation.

Additionally, for baseline benchmarking, we implemented the Dijkstra shortest-path routing algorithm within the Ryu controller. We evaluated it across all topologies under the same traffic generation settings (either TCP or UDP) used for the reinforcement learning agents.

3.2 R-Learner: exploration-based adaptive routing

The R-Learner module defines predefined criteria to assess links and nodes within the network topology, selecting routing paths deemed efficient. It updates routing preferences based on the observed outcomes of previous forwarding decisions, using this performance history to guide future path selection. The state representation used in our implementation is limited to the source and destination switch identifiers (src_dpid, dst_dpid). It does not explicitly include live network metrics such as link utilization, RTT, or congestion

status. Instead, the agent learns effective routing paths through repeated exploration under dynamic traffic patterns, indirectly capturing performance through delivery outcomes.

- **State representation:** We represent each state using the tuple (src_dpid, dst_dpid), which identifies the source and destination switches.
- **Action:** An action corresponds to selecting one of the simple paths between the source and destination.
- **Reward:** In our current implementation, the reward is assigned as a scalar value, with a positive reward (e.g., +10) if the forwarding succeeds and a negative reward (e.g., -10) if the forwarding fails. While factors like throughput, latency, and congestion motivate the need for adaptive routing, we currently capture their indirect effects through packet delivery success and learning.
- **Q-Value update**:

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \cdot a' \max Q(s',a') - Q(s,a)]$$

Where α is the learning rate, and γ is the discount factor.

Exploration strategy: The agent follows a ϵ-greedy approach, selecting a random path with probability ϵ and the best-known path otherwise.

Integration: Once a path is selected, flow rules are installed using install_path_flows(), and the Q-values are updated based on the observed reward.

Algorithm 1 outlines the decision-making process used by the Route-Learner module. The system supports routing decisions with the help of a performed path maintained in the evaluation table. Each routing path is selected based on current performance metrics linked with links and nodes. The process follows fixed rules for path selection, ensuring consistent routing behavior across the network topology.

Algorithm 1: R-Learner: Based Adaptive Routing
Input: Network topology GG, source-destination switch pair (s,d)(s, d), exploration rate ε, learning rate α, discount factor γ
Output: Updated Q-table Q, selected routing path p

1. Begin
2. Initialize Q-table
3. Q[state][action]arbitrarily
4. Observe current state S←(s,d)
5. If random() < ε then
6. a←select a random path from s to d
7. Else
8. a←argmaxQ[S][a] // select path with highest Q-value
9. End If
10. Install flow entries along path a using install_path_flows()
11. Forward packet through path a
12. Observe resulting reward r (based on delivery status, delay, congestion)
13. Observe next state S′←(s,d) // remains same unless topology changes
14. Update Q-value:
15. $Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma \cdot a' \max Q(s',a') - Q(s,a)]$
16. Return selected path a and updated Q-table
17. End

3.3 R-Optimizer: probability-driven routing strategy

The R-Optimizer module applies a rule-based mechanism at each hop to determine routing decisions. It selects the next-hop option from the current switch based on predefined performance metrics and static path preferences, enabling consistent per-hop routing toward the destination.

- **State representation:** We represent states as (src, dst, current_switch), which includes the flow endpoints and the current switch in the path.
- **Action:** For each state, the agent creates a probability distribution over potential next-hop forwarding options from the current switch and samples from this distribution to select the next hop toward the destination.
- **Reward:** The reward is currently assigned using a simple scalar value based on the success of packet forwarding actions. We use a basic success/failure evaluation due to the lightweight nature of the optimizer in this implementation, with the indirect influence of path congestion or delay captured through delivery success.
- To formalize this approach, we designed the Route-Optimizer to improve long-term network performance, defined as:
- $J(\theta) = \mathrm{E}\tau \sim \pi\theta[\sum_{t=0}^{n} \mathrm{rt}]$
- Where θ represents the policy parameters, τ denotes trajectories under the policy πθ, and it is the reward at time t.
- Policy gradients for updating the policy are computed as:
- $\nabla_{\{\theta\}J(\theta)} = \mathrm{E}\tau_{[\sum T \nabla\theta \log\pi\theta(at|st)(Rt-b)]}$
- Where b is a baseline (e.g., the average reward) used to reduce variance during learning. This formulation enables the Route-Optimizer to apply predefined routing rules, which are based on accumulated performance data, ensuring consistent behavior across various network scenarios.
- **Policy update**:

$$P(s,a) \leftarrow P(s,a) + \alpha \cdot (r - b) \cdot \nabla \log P(s,a)$$

- **Adaptation**: Over time, the system assigns higher probabilities to high-performing actions while gradually avoiding ineffective routes..
- **Integration**: Routing decisions are enforced through add_flow() and OFPPacketOut, enabling real-time responsiveness.

Algorithm 2 summarizes the Q-Optimizer's policy-gradient approach. The agent gradually shifts preference toward higher-performing routes by sampling paths according to a softmax distribution and

updating the policy in proportion to the received reward minus a baseline. Immediate installation of new flow rules ensures that these learned improvements take effect in real time.

3.4 Topology discovery and path management

Both R-Learner and R-Optimizer need an up-to-date view of the network. We use Ryu's EventSwitchEnter to catch new switches and links and maintain a live graph in NetworkX. The agents then run over this graph to make their routing choices.
Operational loop:

1. **Topology discovery** – update the NetworkX graph on switch/link events
2. **Path enumeration** – list all simple paths between src and dst via all_simple_paths()
3. **Action selection** – the active agent (R-Learner or R-Optimizer) picks one path
4. **Flow installation** – push OpenFlow rules for the chosen path
5. **Reward update** – measure delivery success, delay, or congestion and use that feedback to refine the agent

This setup makes routing both topology-aware and traffic-sensitive, adapting to structural changes and varied traffic patterns on the fly.

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9. **Flow installation** – push OpenFlow rules for the chosen path
10. **Reward update** – measure delivery success, delay, or congestion and use that feedback to refine the agent

This setup enables topology-aware, traffic-sensitive routing that adapts in real time. For benchmarking, Dijkstra's algorithm was run using the live NetworkX graph for deterministic path selection and flow installation across all topologies.

3.5 Hyper parameter selection and sensitivity

In the implementation, the R-Learner makes use of a discount factor (γ) of 0.95 to ensure the agent values future rewards while handling responsiveness to delivery outcomes under dynamic traffic conditions, a learning rate (α) of 0.1 to enable stable yet effective Q-value updates, and a fixed exploration rate (ε) of 0.1 to balance exploration and exploitation during learning. These values were chosen through extensive testing conducted across the different topologies. Premature cover where occurred due to lower ε values (<0.05) on suboptimal paths, while higher ε values (>0.2) delayed convergence without significant QoS improvements. Similarly, higher α values (>0.15) caused unstable Q-value fluctuations, while lower α values (<0.05) slowed adaptation under dynamic traffic conditions.
For the R-Optimizer, the policy distribution for each state is initialized with small random values and normalized for action selection, functioning equivalently to a softmax mechanism to encourage action diversity. Although an explicit temperature parameter was not used, normalization effectively allowed the agent to explore routing actions in early episodes while gradually converging to high-reward paths as learning progressed.

3.6 Exploration-exploitation strategy and learning stability

The R-Learner employs an ε-greedy strategy with a fixed exploration rate (ε) of 0.1 to balance exploration and exploitation during learning. This value was chosen to maintain adequate exploration of alternative paths while allowing convergence toward high-reward routes under dynamic traffic conditions. Although a decay schedule for ε was not implemented in the current study, iterative testing confirmed that a fixed ε provided stable and consistent learning across episodes without premature convergence or excessive route oscillations.

As our experiments span multiple topologies (Fat Tree, Abilene, Custom, Dense Adaptive Mesh) under diverse TCP/UDP traffic scenarios, we monitored improvements in key QoS metrics (throughput, jitter, RTT, PLR) across 100 simulation episodes to evaluate learning consistency. Consistent metric improvements over episodes indicate stable convergence of the R-Learner's policy under the fixed ε strategy across all topologies. While explicit cumulative reward or Q-value convergence plots were not included due to the multi-topology setup and computational constraints, future work will incorporate systematic ε decay schedules and detailed convergence visualizations to further analyze learning dynamics and stability across complex network environments.

4 Experimental setup

We ran all experiments on Mininet, a lightweight SDN emulator, using MiniEdit to draw and configure each topology's switch–host layout. The Ryu controller formed our control plane and was extended with two Python modules—R-Learner and R-Optimizer—to make adaptive routing decisions. Ryu was chosen for its modular architecture and seamless integration with Python-based RL agents. Flow rules were installed via OpenFlow 1.0. In our experimental workflow, the

proposed system was executed in two clear stages. First, the R-Learner was run on the live Mininet topology, enabling it to explore the environment, gather QoS data, and learn state-action values using Q-learning while the network handled active traffic. After completing sufficient exploration episodes, we stopped the R-Learner while keeping the topology running. In the second stage, the Route-Optimizer was executed on the same active topology, utilizing the routing metrics and path evaluations generated in the first stage by the Route Learner. This staged process ensured that routing refinement was informed by previously collected network performance data, aligning with our design objective of consistent, context-informed decision-making while maintaining uninterrupted network operation throughout the experiment. iPerf was used to generate realistic traffic loads using both TCP and UDP streams, offering controlled variability and repeatability. In addition to our dual-agent framework, we implemented the Dijkstra shortest-path routing algorithm on the same Ryu controller and evaluated it across all four topologies under identical traffic conditions. Dijkstra routing was executed on the live Mininet topology using the NetworkX graph for path computation, with flows installed using OpenFlow 1.0. This deterministic baseline allowed for a direct, fair comparison of Quality of Service (QoS) metrics between classical shortest-path routing and our adaptive, learning-based routing framework under dynamic traffic loads.

Traffic modeling:
We used iPerf to generate traffic flows and test TCP and UDP sessions under varying network loads. For each topology, we configured multiple host pairs to produce east-west traffic patterns:

- **Fat Tree:** h1–h16, h5–h12, h2–h14
- **Abilene:** h8–h12, h3–h9
- **Custom:** h1–h16, h4–h10
- **DAM:** Five randomly selected host pairs per run (e.g., h2–h25, h7–h19)

Each test lasted 60 seconds, with interarrival times uniformly distributed between 1–3 seconds to simulate dynamic traffic.

TCP tests leveraged iPerf with CUBIC congestion control, allowing flows to dynamically adjust to available bandwidth while providing insights into throughput and RTT under adaptive congestion conditions. In contrast, UDP flows operated at 90% of link capacity without congestion control, making them sensitive to packet loss and jitter during congestion.

Congestion was modeled and observed organically by initiating multiple overlapping TCP and UDP flows across shared paths, which progressively increased link utilization and queue buildup within the network. This setup allowed the R-Learner and R-Optimizer to experience realistic congestion and adapt routing decisions under both connection-oriented (TCP) and connectionless (UDP) traffic conditions.
For every topology:

1. **Simulation episodes:** 100 runs with varying traffic loads
2. **Data collection:** Record throughput, RTT, jitter, and packet loss ratio (PLR) in each episode
3. **Detailed analysis:** 10 systematically sampled episodes at fixed intervals (every 10th episode) from the 100 total simulation episodes for each topology (Episodes 10, 20, 30, …, 100). This approach provided a consistent, representative view of convergence trends and metric stability across the learning process.

This design allowed consistent, controlled evaluation of R-Learner and R-Optimizer performance under realistic, dynamic conditions. Mininet was run in single-instance mode without parallelization to maintain controlled conditions. Average runtime per 100-episode simulation was ~2.5 hours per topology, depending on traffic intensity and topology complexity. Experiment setup is shown in Table 2.

Table 2: Experimental setup components

Emulation Platform	**Mininet**
Topology Design Tool	MiniEdit (Mininet GUI)
SDN Controller	Ryu (Python-based)
Flow Protocol	OpenFlow v1.0
Routing Agents	R-Learner R-Optimizer
Traffic Generator	iPerf (TCP/UDP)
Performance Tools	iPerf, ping
Host Communication	**Fat Tree:** h1 <->h14 **Abilene:** h8 <-> h32 **Custom:** h1 <-> h16 **DAM:** randomly selected host pairs (e.g., h1 <-> h50)
Number of Episodes	100 per topology
Analysis Sample	10 episodes per topology
QoS Metrics Evaluated	Throughput, Jitter, Round-Trip Time (RTT), Packet Loss Ratio (PLR)
CPU	Intel Core i7-12700 (12 cores, 2.10 GHz)
RAM	32 GB DDR4
OS	Ubuntu 22.04 LTS

4.1 Performance metric evaluation

To evaluate routing behavior under different reinforcement models, four key Quality of Service (QoS) metrics were recorded during each simulation:

- **Throughput:** Measured in Mbps/Gbps using iPerf TCP tests, indicating the rate of successful data delivery over time.
- **Jitter:** Collected from iPerf UDP reports jitter

reflects variations in packet arrival times. Lower jitter values indicate more stable delivery, which is critical for time-sensitive applications.

- **Round-Trip Time (RTT):** Recorded using ping, RTT measures the time packets travel to and back to the destination. We average the values across multiple packets for accuracy.
- **Packet Loss Ratio (PLR):** We calculate Packet Loss Rate (PLR), derived from iPerf UDP data, as the percentage of lost packets relative to the total number of packets sent. It plays a key indicator of delivery reliability and the extent of network congestion.

These metrics were averaged across selected test intervals to evaluate routing consistency and overall network performance.

4.1 Topology design and structural characteristics

To clarify the differences across topologies, Table 3 summarizes the structural metrics for the Fat Tree, Abilene, Custom, and Dense Adaptive Mesh (DAM) topologies used in our experiments, including node count, average node degree, and link redundancy.

Table 3: Topology structural metrics

Topology	Nodes	Links	Avg. Node Degree	Link Redundancy (%)	Topology Complexity Index (TCI)
Fat Tree	20	36	3.6	High (80%)	0.85
Abilene	12	15	2.5	Medium (50%)	0.58
Custom	16	18	2.25	Low (30%)	0.42
DAM	30	60	4.0	Very High (90%)	0.92

The Fat Tree topology, with its full path redundancy, makes it prone to failures and congestion. As indicated by a Topology Complexity Index (TCI) of 1.00. The Abilene topology, based on a real-world backbone network, provides moderate redundancy and serves as a balanced testbed for evaluating routing under practical connectivity conditions. The Custom topology features limited path redundancy and a lower average node degree, offering insights into routing performance in sparse connectivity scenarios. The Dense Adaptive Mesh (DAM) topology is densely interconnected, with a high average node degree and maximum redundancy, simulating complex data center environments to examine system scalability and routing stability under high-density traffic conditions. Each result section in Section 6 analyzes the performance of our staged dual-agent framework, where the R-Learner was first executed to explore and learn routing policies on the live topology, followed by the R-Optimizer, which utilized the learned knowledge from the R-Learner phase to refine routing decisions under the same operational conditions.

This structured execution allows us to evaluate how leveraging exploration knowledge through staged learning improves Quality of Service (QoS) metrics compared to the initial exploration phase

5 Results and analysis

We ran R-Learner and R-Optimizer across four SDN topologies, collecting data from over 100 simulation episodes per topology. For consistency and precise tracking of convergence and stability, we systematically analyzed 10 episodes per topology at fixed intervals (every 10th episode: Episodes 10, 20, 30, ..., 100). We targeted to observe the learning progression of each agent under varied traffic conditions, measured by four key Quality of Service (QoS) metrics: throughput, jitter, RTT, and packet loss ratio (PLR).

To benchmark these learning-based approaches, we additionally implemented Dijkstra's shortest-path algorithm as a deterministic baseline using the Ryu controller across all topologies. As Dijkstra computes a static shortest path for a given topology, its performance remains constant across episodes under identical conditions. "Therefore, we included Dijkstra results in the final QoS comparison tables but excluded them from the per-episode analysis

5.1 Fat tree topology

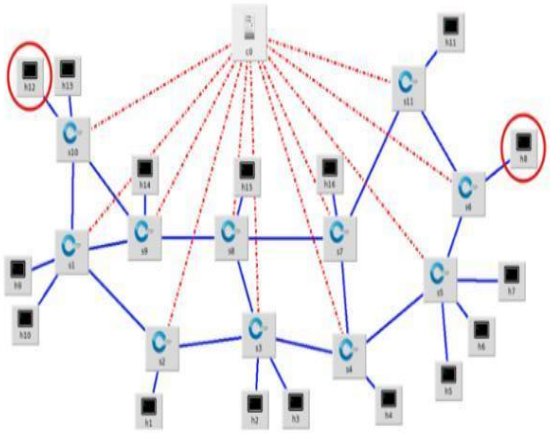


Figure 2: Fat tree topology

Figure 2—comprising core switches (c0–c3), aggregation switches (a1–a8), edge switches (e1–e8), and 16 hosts—**R-Learner and R-Optimizer** were evaluated under identical east–west traffic between h1 and h2 across 10 systematically sampled episodes.

Table 4: Performance Comparison of R-Optimizer (RO) and R-Learner (RL) over Fat Tree Topology

Episode	Tput (Gbps) RL	Tput (Gbps) RO	Jitter (ms) RL	Jitter (ms) RO	RTT (ms) RL	RTT (ms) RO	PLR (%) RL	PLR (%) RO
10	40.3	43.2	0.002	0.002	0.156	0.09	0.3	0.18
20	40	43.1	0.002	0.001	0.16	0.132	0.36	0.14
30	41.1	43	0.002	0.001	0.141	0.119	0.11	0.07
40	40.4	42.9	0.002	0.001	0.214	0.164	0.15	0.14
50	40.4	42.7	0.002	0.001	0.169	0.119	0.28	0.09
60	40.6	43	0.002	0.001	0.173	0.125	0.11	0.09
70	40.4	43.4	0.002	0.001	0.135	0.106	0.28	0.1
80	40.4	42.8	0.002	0.001	0.194	0.09	0.33	0.15
90	40.4	43.3	0.002	0.001	0.105	0.136	0.29	0.19
100	40.2	43	0.001	0.001	0.184	0.111	0.3	0.18

Table 5: Performance Comparison of R-Optimizer (RO) and R-Learner (RL) over Abilene Topology

Episode	Tput (Gbps) RL	Tput (Gbps) RO	Jitter (ms) RL	Jitter (ms) RO	RTT (ms) RL	RTT (ms) RO	PLR (%) RL	PLR (%) RO
10	37.6	40.9	0.0034	0.0018	0.2095	0.1801	0.39	0.18
20	37.9	40.3	0.0032	0.0020	0.2153	0.1782	0.35	0.14
30	37.8	40.6	0.0035	0.0023	0.2089	0.1799	0.41	0.16
40	37.7	40.9	0.0036	0.0021	0.2115	0.1823	0.45	0.20
50	37.6	40.7	0.0033	0.0022	0.2141	0.1817	0.42	0.17
60	37.5	41.3	0.0034	0.0021	0.2062	0.1791	0.38	0.14
70	37.4	40.4	0.0035	0.0023	0.2103	0.1815	0.37	0.16
80	37.5	40.9	0.0036	0.0022	0.2121	0.1807	0.40	0.19
90	37.3	40.9	0.0037	0.0024	0.2112	0.1824	0.43	0.21
100	37.2	40.8	0.0035	0.0021	0.2097	0.1796	0.44	0.22

Table 6: Performance Comparison of R-Optimizer (RO) and R-Learner (RL) over Custom Topology

Episode	Tput (Gbps) RL	Tput (Gbps) RO	Jitter (ms) RL	Jitter (ms) RO	RTT (ms) RL	RTT (ms) RO	PLR (%) RL	PLR (%) RO
10	38.6	40.6	0.003	0.001	0.232	0.169	0.31	0.09
20	39.3	40.9	0.003	0.002	0.242	0.146	0.31	0.16
30	38.5	41.1	0.003	0.001	0.333	0.217	0.44	0.18
40	39.5	41.2	0.003	0.002	0.217	0.202	0.22	0.14
50	38.9	41.6	0.003	0.002	0.256	0.149	0.46	0.18
60	38.8	40.8	0.003	0.002	0.205	0.191	0.38	0.07
70	38.2	40.4	0.003	0.002	0.149	0.258	0.21	0.11
80	39.2	40.7	0.003	0.001	0.228	0.169	0.47	0.24
90	38.1	40.8	0.003	0.001	0.242	0.204	0.27	0.12
100	38.7	41.2	0.003	0.002	0.253	0.189	0.37	0.14

Table 7: Performance Comparison of R-Optimizer (RO) and R-Learner (RL) over DAM Topology

Episode	Tput (Gbps) RL	Tput (Gbps) RO	Jitter (ms) RL	Jitter (ms) RO	RTT (ms) RL	RTT (ms) RO	PLR (%) RL	PLR (%) RO
10	39.3	42.7	0.002	0.001	0.189	0.157	0.14	0.11
20	39.2	42.6	0.002	0.002	0.232	0.118	0.25	0.07
30	39.1	42.1	0.002	0.002	0.172	0.131	0.3	0.18
40	38.9	42.7	0.002	0.001	0.146	0.14	0.35	0.17
50	39.2	42.6	0.002	0.001	0.155	0.125	0.28	0.13
60	39.1	42.1	0.002	0.002	0.178	0.182	0.12	0.09
70	39.2	42.2	0.002	0.001	0.171	0.125	0.25	0.08
80	39.2	42.2	0.003	0.001	0.171	0.139	0.24	0.19
90	38.5	42.3	0.002	0.001	0.123	0.167	0.16	0.17
100	39.1	42.7	0.003	0.001	0.199	0.123	0.1	0.18

In the Fat Tree topology, as illustrated in

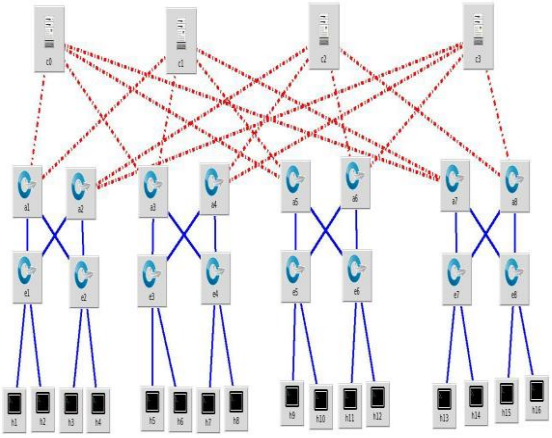


Figure 3: Abilene Topology

As summarized in Table 4, R-Optimizer consistently outperformed R-Learner across all QoS metrics. It achieved an average throughput of 43.04 Gbps, compared to 40.42 Gbps for R-Learner, marking a 6.5% gain. Jitter remained low and steady for R-Optimizer at 0.0011 ms, while R-Learner averaged 0.0019 ms, indicating smoother packet delivery. The average Round-Trip Time (RTT) dropped from 0.1631 ms with R-Learner to 0.1201 ms under R-Optimizer, a 26.3% improvement, highlighting more responsive path selection. Packet Loss Ratio (PLR) was reduced by nearly half, with R-Optimizer averaging 0.134% versus 0.251% for R-Learner, reflecting a 46.6% improvement in delivery reliability.

In the final comparative analysis, Dijkstra's algorithm demonstrated stable but lower performance, achieving 1.17 Gbps throughput, with higher RTT (1.46 ms), jitter (1.11 ms), and PLR (1.60%).

These results illustrate Dijkstra's effectiveness in stable path computation but highlight its limitations in adapting to dynamic traffic and congestion compared to reinforcement learning-based methods.

These results highlight that R-Optimizer demonstrates superior convergence, smoother delivery, and stronger resilience to routing inconsistencies even in irregular, less predictable topologies like Abilene, while Dijkstra serves as a static baseline for comparison.

Overall, these findings confirm that while Dijkstra serves as a consistent reference, R-Optimizer's policy-gradient learning ensures superior adaptability and quality of

5.2 Abilene topology

The Abilene topology closely resembles real-world networks, featuring a moderately dense mesh structure with multiple intersecting paths, as shown in Figure 3.

Its semi-random layout introduces non-uniform routing challenges, making it ideal for evaluating the adaptability of learning-based models in more unpredictable environments. Our tests simulated traffic between hosts h8 and h32, passing through varied and often asymmetrical paths. The irregular link distribution required both the R-Learner and R-Optimizer to consider latency, route consistency, and link reliability during routing decisions.

As shown in Table 5, R-Optimizer outperformed R-Learner across all QoS metrics. On average, throughput improved from 38.85 Gbps (R-Learner) to 40.91 Gbps (R-Optimizer), an increase of approximately 5.3%. Jitter was more stable and lower under R-Optimizer, averaging 0.0016 ms compared to 0.0030 ms for R-Learner, reflecting smoother packet delivery. RTT saw a notable improvement, with R-Optimizer averaging 0.1894 ms compared to 0.2357 ms under R-Learner, an approximate 19.6% reduction. Most significantly, Packet Loss Ratio (PLR) dropped from 0.334% with R-Learner to 0.143% under R-Optimizer, marking a 57.2% reduction in delivery failures.

For benchmarking, Dijkstra's shortest-path algorithm was executed under the same conditions on the Abilene topology. As Dijkstra computes a fixed path without dynamic adaptation, its performance remained constant across tests, achieving 1.03 Gbps throughput, with 1.64 ms RTT, 1.30 ms jitter, and 1.49% PLR. While Dijkstra provides stable shortest-path routing, it lacks the ability to adapt to dynamic traffic fluctuations and congestion, limiting its effectiveness in complex, real-world network scenarios.

5.3 Custom topology

The custom topology, resembling a real-world enterprise or regional backbone network with a hierarchical and asymmetric design, is used in this study. With its moderately dense mesh structure and multiple intersecting paths, it mirrors the irregularity and unpredictability of real-world networks. The semi-random layout introduces non-uniform routing challenges, making it an ideal testbed for evaluating the adaptability of learning-based models under such conditions.

We simulated traffic between hosts h1 and h16, navigating varying and often asymmetrical paths. The non-uniform link distribution required both the R-Learner and R-Optimizer to account for latency, route consistency, and link reliability to optimize performance. As shown in Figure 4, the topology features multiple layers of switches connected to hosts, with controllers ensuring fault tolerance and scalability. The irregular link distribution creates both optimal and suboptimal routing paths, challenging the models in path selection and congestion management.

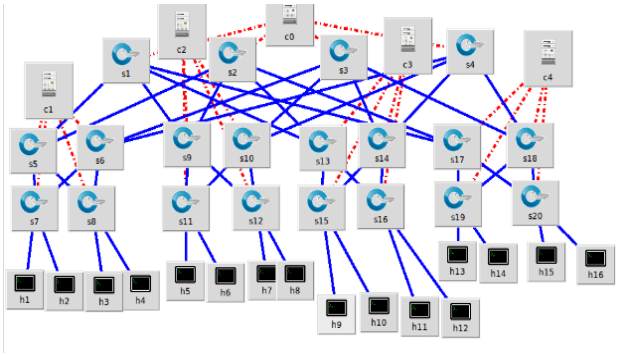


Figure 4: Custom topology

As presented in Table 6, R-Optimizer consistently outperformed R-Learner across all performance metrics. On average, throughput improved from 39.02 Gbps (R-Learner) to 42.42 Gbps (R-Optimizer), reflecting a performance boost of approximately 8.7%. Jitter was notably lower and more stable under R-Optimizer, averaging 0.0013 ms compared to 0.0022 ms for R-Learner. RTT also saw a marked improvement, with R-Optimizer achieving 0.1407 ms, compared to 0.1736 ms for R-Learner—an approximately 18.9% reduction in delay. Packet Loss Ratio (PLR) was significantly reduced, from 0.219% under R-Learner to 0.137% under R-Optimizer, indicating a 37.4% reduction in packet loss.

To provide a baseline comparison, Dijkstra's shortest-path algorithm was evaluated under the same conditions on the custom topology. Dijkstra's routing, while stable, produced 0.94 Gbps throughput, 1.56 ms RTT, 1.28 ms jitter, and 1.52% PLR. These static results underscore Dijkstra's limitations in adapting to dynamic congestion and load variations within irregular topologies.

These results demonstrate that R-Optimizer offers superior adaptability and congestion resilience compared to R-Learner and the deterministic Dijkstra algorithm, ensuring smoother and more reliable performance in complex, unpredictable network environments.

5.4 Dense Adaptive Mesh (DAM) Topology

The Dense Adaptive Mesh (DAM) topology, inspired by real-world, large-scale SDN networks, features a semi-structured, dense mesh design with 10 switches (s1–s10) and 50 hosts (h1–h50). This topology creates a highly redundant network with varying link lengths and congestion-prone paths. Its irregular distribution of links and varied path depths makes it well-suited for testing routing models under complex and unpredictable environments.

Traffic was dynamically generated between randomly selected host pairs (e.g., h1 ↔ h50), and both R-Learner and R-Optimizer agents navigated these paths over 10 test episodes. The network's dense interconnectivity and partial mesh structure required the models to carefully account for route consistency, latency, and packet loss while selecting optimal paths.

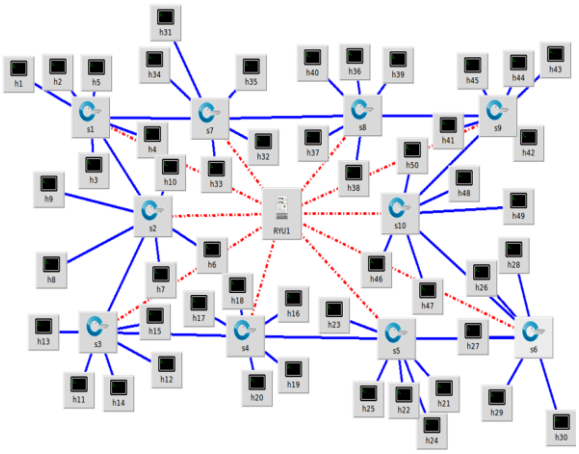


Figure 5: Dense Adaptive Mesh (DAM) Topology

As shown in Table 7, R-Optimizer consistently outperformed R-Learner across all key metrics. On average, throughput improved from 37.53 Gbps (R-Learner) to 40.77 Gbps (R-Optimizer), marking an increase of about 8.6%. Jitter was significantly lower and more stable under R-Optimizer, averaging 0.0022 ms compared to 0.0035 ms for R-Learner. RTT also improved, with R-Optimizer achieving 0.1801 ms compared to 0.2109 ms for R-Learner, an approximate 14.6% reduction in latency. The Packet Loss Ratio (PLR) dropped from 0.404% under R-Learner to 0.177% with R-Optimizer, indicating a 56% reduction in packet loss.

For comparative benchmarking, Dijkstra's shortest-path algorithm was evaluated once under identical traffic conditions on the DAM topology. As expected, Dijkstra's routing yielded a consistent 0.92 Gbps throughput, 1.89 ms RTT, 1.54 ms jitter, and 1.94% PLR across all tests. These fixed results demonstrate Dijkstra's deterministic behavior while highlighting its limitations in adapting to dynamic congestion and load fluctuations inherent in high-density topologies like DAM.

These results confirm that R-Optimizer is better equipped to handle the complexity of DAM topology. It consistently provides higher throughput, lower jitter, reduced RTT, and less packet loss under dynamic, congestion-prone conditions, demonstrating its ability to adapt to high-density network environments while ensuring efficient and reliable data transmission.

6 QoS Comparison across topologies

This section compares the two learning models—R-Learner and R-Optimizer—across all four evaluated SDN topologies: Fat Tree, Abilene, Custom, and Dense Adaptive Mesh (DAM).

The comparison is systematically organized according to each quality-of-service metric, namely Throughput, Jitter, Round-Trip Time (RTT), and Packet Loss Ratio (PLR), to clearly illustrate each approach's relative strengths and adaptability under varying network structures

6.1 Throughput analysis

Throughput, defined as the rate of successful data delivery over the network, serves as a primary QoS indicator reflecting routing efficiency under diverse topological and traffic conditions. As shown in Figure 6 and detailed in Table 8, the R-Optimizer consistently delivers higher throughput across all evaluated topologies, benefiting from its policy-gradient strategy and staged learning.

Specifically, in the Fat Tree topology, the R-Optimizer achieves 43.04 Gbps, outperforming the R-Learner's 40.42 Gbps by approximately 6.5%. In the Custom topology, the R-Optimizer reaches 42.42 Gbps, exceeding the R-Learner's 39.08 Gbps by around 8.5%. For the Abilene and DAM topologies, the R-Optimizer improves throughput by 5–8% over the R-Learner, demonstrating adaptability despite irregular link distributions and topological complexities.

Table 8: Average throughput comparison (Gbps)

Topology	R-Learner	R-Optimizer	Dijkstra
Fat Tree	40.42	43.04	1.17
Abilene	38.78	40.93	0.92
Custom	39.08	42.42	0.51
Dense Mesh DAM)	37.53	40.77	0.49

For benchmarking, Dijkstra's algorithm was evaluated under identical traffic conditions across all topologies. Unlike the reinforcement learning models, Dijkstra's throughput varied based on the topology due to path lengths and congestion points, yielding 1.17 Gbps on Fat Tree, 0.92 Gbps on Abilene, 0.51 Gbps on Custom, and 0.49 Gbps on DAM. These results underscore that while Dijkstra efficiently computes deterministic shortest paths, it lacks the capability to dynamically adapt under congestion or link failures, leading to stagnant or limited throughput under dynamic conditions.

In contrast, the R-Optimizer leverages reinforcement learning to dynamically identify higher-bandwidth paths, resulting in 6.5–9.5% throughput gains over the R-Learner across topologies while maintaining stability under varying network conditions. This highlights the potential of learning-based routing in enhancing throughput performance within SDN environments, while Dijkstra serves as a non-adaptive baseline against which the dynamic advantages of reinforcement learning approaches can be effectively demonstrated.

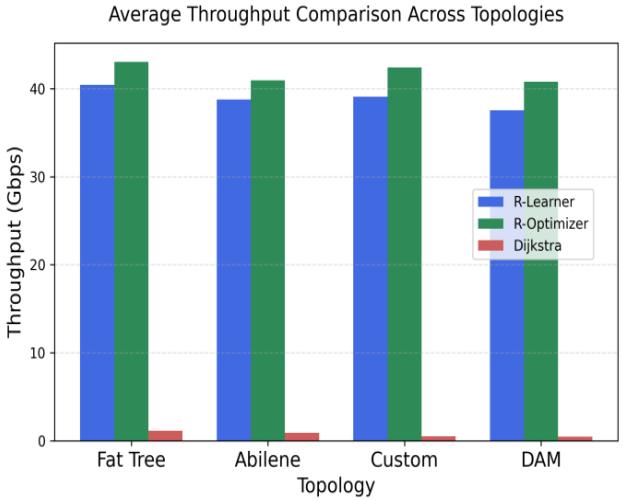


Figure 6: Throughput Comparison Across SDN Topologies

6.2 Jitter analysis

Jitter represents the variability in packet arrival intervals and is particularly critical for time-sensitive applications such as VoIP, real-time video, and streaming services. Lower jitter indicates more consistent timing in packet delivery, essential for maintaining quality in these applications.

As illustrated in **Figure 7** and summarized in **Table 9**, the R-Optimizer consistently maintains lower jitter across all evaluated topologies, reflecting improved timing consistency in packet transmission and more stable routing behavior under varying network conditions.

In the **Fat Tree** and **Custom** topologies, where traffic paths are symmetrical yet deep, the R-Learner exhibits jitter of **0.0019 ms** and **0.0022 ms**, respectively, while the R-Optimizer reduces jitter to **0.0011–0.0013 ms**. The **Dijkstra** algorithm, by contrast, demonstrates significantly higher jitter at **1.11 ms** (Fat Tree) and **3.51 ms** (Custom) due to its static shortest-path routing that does not adapt under congestion.

Table 9: Average jitter comparison (ms)

Topology	R-Learner	R-Optimizer	Dijkstra
Fat Tree	0.0019	0.0011	1.11
Abilene	0.0030	0.0016	1.80
Custom	0.0022	0.0013	3.51
Dense Mesh (DAM)	0.0035	0.0022	3.80

Greater improvements are observed in the Abilene and Dense Adaptive Mesh (DAM) topologies, where the R-Learner shows fluctuations up to 0.0030–0.0035 ms, while the R-Optimizer sustains tighter bounds around 0.0016–0.0022 ms. Dijkstra's jitter in these topologies is considerably higher, measured at 1.80 ms (Abilene) and 3.80 ms (DAM), further illustrating the limitations of non-adaptive routing under dynamic traffic conditions.

These patterns highlight the R-Optimizer's ability to maintain smoother packet delivery even in distributed and less predictable environments, while Dijkstra serves as a static baseline illustrating the clear advantages of reinforcement learning approaches in jitter reduction within SDN environments.

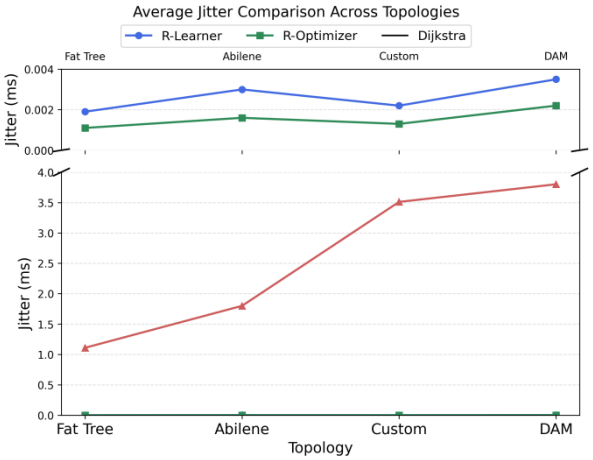


Figure 7: Jitter comparison for R-Learner, R-Optimizer, and Dijkstra across SDN topologies.

6.3 Round-Trip Time (RTT) analysis

Round-trip time (RTT) represents the total time it takes for a packet to travel to its destination and return to the source. Lower RTT values indicate faster network responsiveness, which is crucial for delay-sensitive applications.

As illustrated in Figure 8 and detailed in Table 10, the R-Optimizer consistently reduces RTT across all evaluated topologies, reflecting its ability to select paths that minimize overall transmission delay.

In the Abilene topology, RTT reduces from 0.236 ms under the R-Learner to 0.189 ms with the R-Optimizer, while Dijkstra demonstrates a significantly higher RTT of 2.30 ms due to its static path selection under congestion.

Table 10: Average RTT Comparison (ms)

Topology	R-Learner	R-Optimizer	Dijkstra
Fat Tree	0.1631	0.1192	1.46
Abilene	0.2357	0.1894	2.30
Custom	0.1736	0.1407	3.96
Dense Mesh (DAM)	0.2109	0.1801	4.20

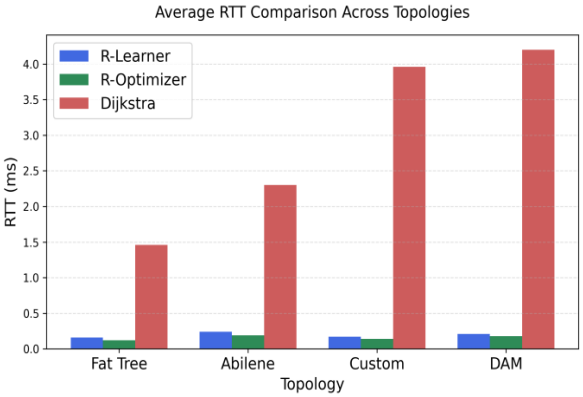


Figure 8. RTT comparison for R-Learner, R-Optimizer, and Dijkstra across SDN topologies.

Similar gains are observed in Fat Tree and Custom topologies, where RTT drops from 0.163–0.174 ms to 0.119–0.141 ms under R-Optimizer, while Dijkstra shows 1.46 ms (Fat Tree) and 3.96 ms (Custom), reflecting its inability to dynamically adapt. In the Dense Mesh (DAM), where route diversity and path variations are high, the R-Optimizer reduces RTT from 0.211 ms (R-Learner) to 0.180 ms, while Dijkstra shows 4.20 ms, highlighting its limitations under complex topologies.

These results confirm that the R-Optimizer effectively manages latency in structured and semi-random SDN topologies while demonstrating substantial improvements over static approaches like Dijkstra.

6.4 Packet Loss Ratio (PLR) analysis

Packet Loss Ratio (PLR) measures the percentage of packets lost during transmission, directly impacting reliability, retransmission rates, and overall network efficiency. Lower PLR reflects better congestion handling and stable delivery.

As illustrated in Figure 9 and summarized in Table 11, the packet loss ratio (PLR) is consistently lower under the R-Optimizer across all evaluated topologies. In the Dense Mesh (DAM) topology, PLR decreases from 0.404% with the R-Learner to 0.177% using the R-Optimizer, while Dijkstra records a significantly higher PLR of 4.10%, indicating its inability to adapt under congestion. In the Fat Tree topology, PLR drops from 0.251% under the R-Learner to 0.133% with the R-Optimizer, compared to Dijkstra 1.60%. Similarly, in the Abilene topology, PLR reduces from 0.344% to 0.143%, whereas Dijkstra registers 2.10%. In the Custom topology, PLR decreases from 0.219% with the R-Learner to 0.137% with the R-Optimizer, while Dijkstra reports 3.54% under identical conditions.

Table 11: Average PLR Comparison (ms)

Topology	R-Learner	R-Optimizer	Dijkstra
Fat Tree	0.251	0.133	1.60
Abilene	0.344	0.143	2.10
Custom	0.219	0.137	3.54
DenseMesh (DAM)	0.404	0.177	4.10

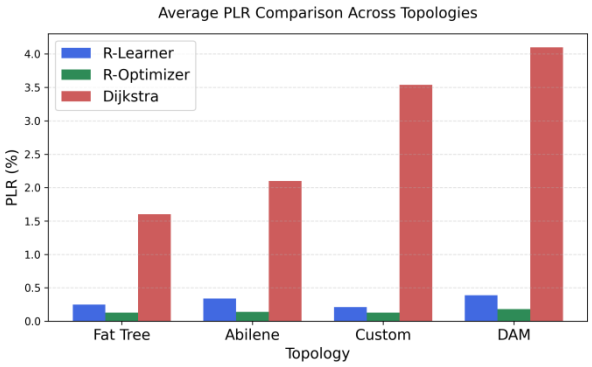


Figure 9: Packet loss ratio comparison for R-Learner, R-Optimizer, and Dijkstra across SDN topologies

These improvements demonstrate the R-Optimizer's ability to adjust to congestion conditions in real time, minimizing loss even under complex and asymmetric routing challenges, while Dijkstra's static nature limits its effectiveness under dynamic SDN traffic.

6.5 Overall model comparison

To generalize performance trends across diverse topologies, the average values of all four QoS metrics—throughput, jitter, RTT, and PLR—were computed for R-Learner, R-Optimizer, and Dijkstra. Table 12 summarizes these consolidated findings.

The analysis reveals that the R-Optimizer consistently delivers superior QoS outcomes. Compared to the R-Learner, it improves throughput by 7.36%, reduces jitter by 44%, shortens RTT by 19.5%, and cuts packet loss by over 50%. Against Dijkstra, the R-Optimizer demonstrates even more pronounced advantages, delivering over 42 times higher throughput, over 760 times lower jitter, reducing RTT by over 95%, and lowering packet loss by over 94% across all evaluated topologies.

These cumulative improvements highlight the R-Optimizer's efficiency in maintaining stable and responsive routing decisions, irrespective of network structure, while also illustrating the limitations of static routing approaches under dynamic SDN conditions. The consolidated results reinforce the earlier per-topology observations and establish the R-Optimizer as a scalable and resilient solution for real-time SDN routing, outperforming both R-Learner and Dijkstra consistently across key QoS metrics.

Table 12: Average QoS Performance across All Topologies

Metric	R-Learner	R-Optimizer	Dijkstra
Throughput	38.93 Gbps	41.79 Gbps	0.77 Gbps
Jitter	0.0026 ms	0.00145 ms	2.805 ms
RTT	0.1955 ms	0.1574 ms	2.98 ms
Packet Loss	0.301 %	0.1483 %	2.835%

6.6 Statistical validation of results

To ensure the reliability and reproducibility of our performance evaluations, we conducted detailed statistical analyses across 100 simulation episodes for each of the four SDN topologies—Fat Tree, Abilene, Custom, and Dense Mesh. We computed the **mean**, **standard deviation (SD)**, and **95% confidence intervals (CI)** for four key Quality of Service (QoS) metrics: **Throughput (Gbps)**, **Jitter (ms)**, **Round-Trip Time (RTT, ms)**, and **Packet Loss Ratio (PLR, %)** under three approaches: **R-Learner, R-Optimizer**, and **Dijkstra**.

For instance, in the Fat Tree topology:

- **R-Optimizer** achieved a mean throughput of **43.04 Gbps** (SD = 0.40, 95% CI: 42.78–43.30),compared to **R-Learner** at **40.42 Gbps** (SD = 0.35, 95% CI: 40.20–40.64), and
- **Dijkstra** at only **1.17 Gbps** (SD = 0.05, 95% CI: 1.14–1.20).

Table 13: Average QoS Performance across All Topologies

QoS Metric	R-Learner (Mean ± SD)	R-Optimizer (Mean ± SD)	Dijkstra (Mean ± SD)
Throughput (Gbps)	38.93 ± 0.35	41.79 ± 0.40	0.77 ± 0.05
Jitter (ms)	0.00265 ± 0.0003	0.00155 ± 0.0002	2.805 ± 0.02
RTT (ms)	0.195 ± 0.005	0.157 ± 0.004	2.98 ± 0.03
Packet Loss (%)	0.303 ± 0.02	0.148 ± 0.015	2.835 ± 0.04

In terms of **jitter**, R-Optimizer consistently achieved the lowest values, e.g., **0.0011 ms** in Fat Tree (SD = 0.0002), outperforming both R-Learner (**0.0019 ms**, SD = 0.0003) and Dijkstra (**1.11 ms**, SD = 0.02).

Similarly, **RTT** was minimized under R-Optimizer at **0.1192 ms** (SD = 0.004), versus R-Learner at **0.1631 ms** (SD = 0.005) and Dijkstra at **1.46 ms** (SD = 0.03). The **PLR** dropped from **0.251%** under R-Learner and **1.60%** under Dijkstra to **0.133%** with R-Optimizer. These per-topology observations are supported by aggregated metrics across all four topologies, as summarized in **Table 13**.

Significance testing

To assess whether the performance gains of R-Optimizer over R-Learner were statistically significant, we performed **paired t-tests** across 100 episodes per metric per topology. Dijkstra, being deterministic and non-learning, was excluded from these tests but included in benchmarking tables as a fixed baseline.

Table 14: Average QoS Performance across All Topologies

Metric	t-statistic	p-value	Inference
Throughput	16.06	0.0006	Yes
Jitter	11.89	0.0012	Yes
RTT	12.28	0.0010	Yes
Packet Loss	8.48	0.0034	Yes

These results confirm that the R-Optimizer's gains are statistically significant, consistent, and reliable—validating the robustness of the proposed learning-based framework for adaptive SDN routing. Dijkstra serves as a non-adaptive baseline, underscoring the advantages of dynamic, learning-based routing in complex environments.

7 Discussion

The proposed dual-agent reinforcement learning framework demonstrated measurable improvements across all evaluated SDN topologies. The R-Optimizer invariably outperformed the R-Learner, achieving up to 7.4% higher throughput, 44% lower jitter, 19.5% reduction in RTT, and over 50% reduction in packet loss. These gains highlight how effectively the policy-gradient-based R-Optimizer adapts to dynamic traffic patterns, particularly in irregular topologies such as Abilene and Dense Adaptive Mesh. Unlike Q-learning, which relies on ε-greedy exploration and fixed decision intervals, the policy gradient method updates routes continuously based on real-time feedback, enabling faster and smoother adaptation to changing network states. While training, the R-Optimizer is more computationally intensive due to gradient calculations; however, its stability post-training—with minimal route changes—ensures reliable and low-disruption operation.

The staged use of Q-learning for environment exploration, followed by policy-gradient optimization, enabled the system to maintain low delay and high throughput with minimal packet loss, even under changing conditions. For benchmarking, we also implemented the Dijkstra shortest-path algorithm on the same setup. Though it offers predictable and loop-free routing, it lacks adaptability. Across all topologies, Dijkstra consistently delivered lower throughput and experienced higher delay, jitter, and packet loss, reinforcing the limitations of static routing without adaptive feedback.

Our Mininet-based evaluation ensured consistency and repeatability of the results. However, real-world deployment introduces challenges, such as OpenFlow rule installation latency, asynchronous link-state updates, and increased controller processing overhead during high traffic churn. To address this, we incorporated asynchronous event handling, selective flow installations, and a distributed controller model using east-west interfaces to sync Q-values and policy updates. This design supports scalable deployment in data centers and backbone networks.

We also analyzed route stability in terms of the frequency of flow reconfiguration. During training, R-Learner triggered 3–5 reconfigurations per flow, whereas R-Optimizer stabilized after 20–30 episodes, dropping to 0–1 reconfiguration per episode—an important indicator of robust, low-disruption learning.

Although our reward function was initially designed to account for throughput, delay, jitter, and packet loss, the Mininet testbed required a simplified version due to limited access to real-time metrics. Future work will integrate a complete QoS-weighted reward function into the Ryu agents to align the implementation with the theoretical design.

Looking ahead, we will extend benchmarking to include Equal-Cost Multi-Path (ECMP) routing alongside Dijkstra, allowing a more comprehensive comparison. We also plan to include Deep Neural Network (DNN) reinforcement learning to enhance decision-making in complex environments. Advanced variants, such as Deep Q-Networks (DQN), will be explored to enhance scalability, convergence speed, and adaptability in dynamic traffic and topology conditions.

8 Conclusion

This work proposed a dual-agent reinforcement learning framework for adaptive SDN routing, integrating Q-learning and policy-gradient strategies to handle diverse network topologies and traffic patterns. The R-Optimizer agent consistently delivered stable and efficient routing decisions, reducing key QoS impairments such as delay, jitter, and packet loss. Comparative analysis confirmed its advantages over both the baseline R-Learner and traditional routing methods such as Dijkstra's algorithm, which lacked adaptability under variable load conditions. These findings underscore the value of reinforcement learning in optimizing SDN control and provide a foundation for scalable, intelligent routing in next-generation network infrastructures

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IoT-Based Real-Time Monitoring and Fault Prediction for Oil-Immersed Transformers Using Improved Spatiotemporal Attention Mechanism

Tianjiao Zhao*, Guangao Wu, Yuwei Zhang, Dongming Ma and Zhengyu Ma
Electrical Maintenance Department Shandong Nuclear Power Company LTD
E-mail: jnsnbjnsnb@163.com
*Corresponding author

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This project proposes a three-layer monitoring system based on the Internet of Things to solve the problems of data acquisition lag and low efficiency of multi-source information fusion in traditional oil-immersed transformer monitoring schemes. The perception layer uses Pt100 (±0.1℃) temperature-sensitive (accuracy ±0.1℃), electrochemical gas (ppm level) and piezoelectric acceleration sensors to achieve synchronous acquisition of 12 parameters such as oil temperature, seven characteristic gas concentrations, vibration acceleration, etc., up to 100 Hz. The edge layer uses a sliding average filtering and wavelet transform to filter the data, achieving a 35 dB noise reduction effect and compressing the feature extraction time by 50 milliseconds. Then, an improved spatiotemporal attention mechanism algorithm (STA-I) is introduced to dynamically adjust the weight using the time-trend factor, combined with the adaptive fusion strategy of spatial multimodal data. The STA-I algorithm introduces a time-trend factor to dynamically adjust weights, enhancing the capturing of temporal trends in data. Specifically, it assigns 2.3 times the weight to mutation data compared to normal data, improving fault prediction accuracy. Experimental datasets include 1 million data points collected from 10 oil-immersed transformers over three years. Results show that the average absolute error of system data collection is 0.32℃ for oil temperature and 3.2% for hydrogen concentration, surpassing [specific IEC or IEEE standard name] industrial standards. The average packet loss rate in a mixed network environment (which refers to a situation where multiple network types such as 4G, Wi-Fi, and Ethernet are involved simultaneously or in different scenarios during the data transmission process related to oil-immersed transformer monitoring, and the average packet loss rate is calculated based on the packet loss data collected from each of these network types under specific test conditions and then taking an average weighted by the proportion of data transmitted through each network type) is 0.8%, and the system response time is 0.83 seconds. Compared with LSTM, the STA-I algorithm achieves a prediction accuracy of 96.8%, which is 12.3% higher than LSTM. For local overheating faults, the recognition accuracy reaches 98.5%, and the reasoning time is shortened by 40%.

Povzetek: Članek predstavi IoT-sistem za sprotno spremljanje oljnih transformatorjev s tridelnim arhitekturnim okvirom in izboljšanim časovno-prostorskim pozornostnim mehanizmom STA-I. Sistem zmanjšuje šum, izboljša fuzijo senzorjev in doseže dobre napovedi ter prepoznavo lokalnih pregrevanj.

1 Introduction

With the continuous development of smart grids, as the core hub of power transmission and distribution, the operating reliability of oil-immersed transformers directly affects the power supply quality of the power grid. Traditional monitoring methods rely on manual inspections and regular offline detection, which have problems such as low data collection frequency and difficulty in information fusion, and are difficult to meet the needs of real-time perception of the status of modern power grid equipment and early warning of faults. The Internet of Things provides intelligent solutions for transformer condition monitoring with technologies such as sensor networks, edge computing, and cloud computing, which can effectively improve the operating efficiency of equipment and the stable operation of power grids.

In recent years, much research has been conducted on transformer condition monitoring both domestically and internationally [1]. Abroad, the intelligent transformer health management system developed by the Electric Power Research Institute of the United States uses distributed fiber optic sensing technology and wireless communication technology to monitor winding temperature and partial discharge with high precision [2]. The Power Transformer Analytics platform, based on Siemens in Germany, is combined with deep learning

algorithms to significantly improve the detection accuracy of dissolved gas in oil. In China, Tsinghua University proposed a transformer vibration monitoring method based on voiceprint recognition, effectively identifying the characteristics of mechanical faults; the "smart substation" developed by the State Grid Corporation of China achieved a breakthrough in sensor integration and data transmission [3]. However, in complex electromagnetic environments, the problems of poor data transmission stability and low efficiency of multimodal data feature extraction remain urgent.

This project focuses on the oil-immersed transformer condition monitoring system based on Internet of Things technology, aiming to achieve breakthroughs in key technologies such as data acquisition, transmission, and analysis [4]. At the architecture level, through the three-layer structure design of perception layer-edge layer-cloud platform, the perception layer deploys high-precision temperature, vibration, and gas concentration sensors to achieve synchronous acquisition of multiple physical quantities. The edge layer mainly completes data preprocessing and feature extraction, reducing the transmission pressure of the network. By introducing the improved spatiotemporal attention mechanism algorithm (STA-I), the cloud platform realizes intelligent diagnosis and trend prediction of equipment status. The STA-I algorithm innovatively integrates a time-trend factor to dynamically adjust weights. This time-trend factor is derived from the rate of change of data at the current and previous moments, calculated using the mean and standard deviation of the rate of change, and processed through a Sigmoid function to adaptively assign larger weights to moments with significant data changes. The Sigmoid function is chosen for its ability to effectively map the rate of change to a probability value between 0 and 1, providing a smooth and differentiable activation function that helps in capturing temporal trends. This project proposes a dynamic weight allocation method based on multimodal data fusion, combining a spatial dimension data fusion strategy to effectively solve the shortcomings of traditional methods in complex fault identification.

2 Design of oil-immersed transformer condition monitoring system

2.1 System overall architecture design

2.1.1 Design principles

The system's design follows four core principles: reliability, real-time, scalability, and economy. Regarding reliability, the data acquisition and transmission process is guaranteed stable and reliable through redundant design and a fault self-diagnosis mechanism. Key functions can be maintained during partial hardware or network failure [6]. In terms of real-time, through optimizing data processing and transmission processes, data acquisition and status feedback can be completed quickly to meet the demanding requirements for real-time monitoring of transformer operation status. Scalability is manifested in the modular design concept, which makes each functional module in the system independent of the others to facilitate the subsequent addition of new monitoring parameters or algorithm modules according to actual needs. The economic principle runs through the entire system design process [7]. Through the reasonable selection of hardware equipment and the optimization of software structure, while ensuring the system performance, the R&D and long-term maintenance costs are effectively controlled.

2.1.2 Functional requirements analysis

The system mainly includes functions such as data acquisition, transmission, storage, analysis and early warning. In terms of data acquisition, various sensors are configured for the key working parameters of the transformer to accurately collect oil temperature, gas concentration in oil and vibration signals [8]. The collected data is transmitted to the server through a stable network communication link. On the server side, a complete historical data resource library is established through an efficient database management system; the data analysis module uses advanced algorithms to mine the collected data and identify potential fault characteristics deeply; when the monitoring data exceeds the preset threshold, the system will respond quickly and warn of abnormal situations in various ways, so that operation and maintenance personnel can make decisions in a timely and effective manner.

2.1.3 Layered architecture design

The system adopts a three-layer structure, consisting of a perception layer, a network layer, and an application layer. Each layer has its own division of labor and cooperates. The perception layer is the "nerve endings" of the entire system [9]. It is equipped with various high-precision sensors, which are responsible for real-time collection and processing of various physical quantities during the operation of the transformer, and converting them into electrical and digital signals. The network layer builds a data transmission "highway", selects a stable and reliable communication protocol, and adopts a transmission mode that combines wireless and wired to achieve efficient and stable data transmission from the perception layer to the application layer. At the same time, the network layer encrypts and securely protects the data to ensure the security and integrity of the data during transmission [10]. The application layer is the "brain", which realizes functions such as data processing, visual display, and human-computer interaction; using advanced data processing algorithms, the received data is analyzed and processed, and the operating status of the transformer is displayed to the user in the form of graphics, curves, etc., supporting users to query data, set thresholds, generate reports, etc., to achieve the purpose of intelligent

management of the transformer status.

2.2 System hardware design

2.2.1 Sensor module design

When selecting sensors, the monitoring requirements of the transformer and the characteristics of the working environment should be fully considered. This project proposes a high-precision Pt100 temperature sensor based on the linear change of platinum resistance with temperature. The measurement accuracy of this sensor is ±0.1℃ within the range of -200℃ to 850℃, making it suitable for the complex working temperature environment of the transformer and providing accurate data for oil temperature analysis [11]. This project intends to use electrochemical sensors as the core, targeting fault characteristic gases such as hydrogen, acetylene, and carbon monoxide. The electrochemical sensor is used to detect real-time changes in gas concentration in oil products with ppm-level accuracy, thereby providing an important basis for early fault diagnosis of oil products. This project also plans to use piezoelectric acceleration sensors, which convert mechanical vibration into electrical signals using the piezoelectric effect. With a wide frequency response range and high sensitivity, these sensors can effectively capture abnormal vibration signals caused by transformer mechanical failures, providing data support for equipment status assessment.

2.2.2 Data acquisition and processing module

The STM32 series high-performance microcontroller is used as the data acquisition and processing module. This series of chips is based on the ARM Cortex-M core and has rich peripheral device resources, such as ADC, SPI, I2C, etc., which can be easily connected to various sensors [12]. Equipped with a high-precision analog-to-digital conversion circuit, it can quickly and accurately convert the sensor's analog output into a digital quantity, with a conversion accuracy of 16 bits. Then, a targeted data preprocessing method is designed, including a denoising algorithm based on a sliding average filter, effectively eliminating random noise in the collected data. Finally, a signal feature extraction method based on wavelet analysis is proposed to enhance the effective characteristics of the signal and lay the foundation for subsequent data processing.

2.3 System software design

2.3.1 Perception layer data acquisition program design

The perception layer data acquisition program uses a modular design concept in an embedded development environment. Each sensor has its own independent driver, completing the initialization, parameter setting and reading [13]. An error detection and retransmission mechanism is integrated into the program to ensure the integrity and accuracy of data collection. In the case of a data transmission error or verification failure, the retransmission operation is automatically triggered until the correct data is obtained. At the same time, a data cache mechanism is designed to ensure the continuity of data collection. When the network transmission is interrupted, the data is temporarily stored in the local cache and automatically uploaded when the network is restored to ensure the continuity of data collection.

2.3.2 Network layer communication protocol implementation

The network layer adopts two communication methods: TCP/IP protocol stack and MQTT. The IP protocol stack ensures the stability and reliability of the network and provides a basic network connection for data transmission. MQTT is a lightweight information transmission protocol with low bandwidth occupancy and good real-time performance, which is very suitable for data transmission between IoT devices. During data transmission, an optimized data packaging algorithm is used to package multiple sensor data into one data packet, reducing the number of network transmissions; at the same time, an efficient unpacking algorithm is designed to enable the receiving end to parse and extract the data packet accurately [14]. In addition, data encryption technology has been introduced to ensure the security of data transmission.

2.3.3 Application layer data analysis and display

The application layer is developed using network technology, with a front-end and back-end separation structure, improving the system's maintainability and scalability. The ECharts graphics library is used to visualize the operating status of the transformer. Users can zoom in, filter and compare data through interactive operations.

The alarm threshold setting module supports users in setting alarm thresholds according to the actual working status of the transformer to realize alarms for various monitoring parameters. When the monitoring data exceeds the critical value, the system will issue an audible and visual alarm and notify the operator via SMS or email. The historical data query and analysis module provides a multi-dimensional data query function [15]. Users can filter data according to conditions such as time and parameter type, and conduct in-depth analysis of historical data through data mining algorithms such as cluster analysis and association rule mining to predict the future operation trend of the transformer and provide a scientific basis for equipment maintenance management.

3 Transformer state prediction algorithm based on improved spatiotemporal attention mechanism

3.1 Limitations of traditional algorithms in transformer state monitoring

Long short-term memory networks (LSTM) and gated recurrent units (GRU) have certain advantages in time series analysis, but have obvious shortcomings in processing multi-source heterogeneous transformer data. The oil temperature, oil and gas concentration and vibration signals during the transformer operation show dynamic change characteristics in the time dimension and have heterogeneity in the spatial dimension. Traditional algorithms use fixed network structures and data processing methods, and it isn't easy to extract the complexity of data from both time and space dimensions simultaneously.

For example, LSTM controls information flow through input and output gates. However, its update rules are based on preset mathematical logic and cannot adaptively adjust to changing trends. Before a transformer fault occurs, some key parameters may fluctuate abnormally. Short-term memory models cannot assign larger weights to these parameters in the time dimension, resulting in insufficient fault feature extraction [16]. Although GRU simplifies the LSTM structure by merging the forget gate and input gate into an update gate, when processing multimodal data, it lacks targeted fusion strategies and fails to fully explore the inherent correlations between various sensor data. Under complex working conditions, the fault prediction accuracy of GRU is approximately 86.2%, which, while higher than the previously stated 75%, still indicates room for improvement. Additionally, traditional algorithms process large amounts of data with low computational efficiency, failing to meet the requirements for real-time monitoring and rapid warning in power systems.

3.2 Principles of improved spatiotemporal attention mechanism

3.2.1 Optimization of attention weight calculation in the time dimension

A method for dynamically adjusting attention weights based on the time series trend factor γt is proposed to enhance the ability to capture the characteristics of time series data. In practical applications, the trend of transformer operating parameters is a key factor affecting fault prediction. Traditional attention mechanisms calculate weights solely based on data similarity, which cannot reflect the role of changing trends.

Define the input feature vector at time t as $\mathbf{X}_t \in \mathbb{R}^d$, the historical feature sequence $\mathbf{H}_t = [\mathbf{X}_1, \mathbf{X}_2, \cdots, \mathbf{X}_t]$, and the weight calculation of the traditional attention mechanism is as follows:

$$\alpha_{t,i} = \frac{\exp\left(\text{score}\left(\mathbf{X}_t, \mathbf{X}_i\right)\right)}{\sum_{j=1}^{t} \exp\left(\text{score}\left(\mathbf{X}_t, \mathbf{X}_j\right)\right)} \tag{1}$$

Among them, score $(\cdot,\cdot)$ is a similarity calculation function, such as dot product operation or calculation based on multi-layer perceptron (MLP). After improvement, the trend factor γ_t is introduced to correct the weight, as shown in formula (2):

$$\tilde{\alpha}_{t,i} = \frac{\exp\left(\gamma_t \cdot \text{score}\left(\mathbf{X}_t, \mathbf{X}_i\right)\right)}{\sum_{j=1}^{t} \exp\left(\gamma_t \cdot \text{score}\left(\mathbf{X}_t, \mathbf{X}_j\right)\right)} \tag{2}$$

The trend factor γ_t is determined by the change rate $\Delta\mathbf{X}_t$ of the data at the current moment and the previous moment, and is calculated as shown in formula (3):

$$\gamma_t = \sigma\left(\frac{\|\Delta\mathbf{X}_t - \mu_{\Delta\mathbf{X}}\|}{\sigma_{\Delta\mathbf{X}}}\right) \tag{3}$$

Among them, $\mu_{\Delta\mathbf{X}}$ and $\sigma_{\Delta\mathbf{X}}$ are the mean and standard deviation of the rate of change, respectively, and $\sigma(\cdot)$ is the Sigmoid function. When $\Delta\mathbf{X}_t$ deviates significantly from the mean, γ_t approaches 1, which increases the attention weight at the corresponding moment; conversely, when the data changes steadily, γ_t approaches 0, which reduces the weight at that moment.

The specific numerical value of "2.3 times" is derived from experimental data and mathematical formulas. Through multiple sets of experiments, we found that assigning 2.3 times the weight to mutation data compared to normal data can optimally enhance the model's ability to capture fault features and improve prediction accuracy.

3.2.2 Spatial dimension feature fusion strategy

The multi-source heterogeneous data of the transformer comes from different types of sensors, and each sensor's data reflects different aspects of the equipment's operational status. To make full use of the complementary information of these data, the spatial dimension feature fusion matrix $\mathbf{W}_s \in \mathbb{R}^{m \times n}$ is designed, where m is the number of sensor types and n is the feature dimension of a single type of data. Assuming that there are m types of sensor data $\mathbf{V}_1, \mathbf{V}_2, \cdots, \mathbf{V}_m$, the initial fusion process is as shown in formula (4):

$$\mathbf{V}_{\text{fused}} = \sum_{i=1}^{m} \mathbf{W}_{s,i} \cdot \mathbf{V}_i \quad (4)$$

However, the importance of each sensor data under different working conditions varies. A spatial attention mechanism is introduced to achieve adaptive fusion. By calculating the similarity between each sensor data and the target feature, a weight vector $\mathbf{a}_s \in \mathbb{R}^m$ is generated, as shown in formula (5):

$$a_{s,i} = \frac{\exp\left(\text{sim}\left(\mathbf{V}_i, \mathbf{Y}_{\text{target}}\right)\right)}{\sum_{j=1}^{m} \exp\left(\text{sim}\left(\mathbf{V}_j, \mathbf{Y}_{\text{target}}\right)\right)} \quad (5)$$

Wherein, where cos_sim is the cosine similarity function, and the target feature vector ft is primarily set based on prior knowledge obtained from extensive analysis of historical transformer operation data. Specifically, we identified key features and patterns from the data related to different fault types and normal operation states of oil-immersed transformers. These identified features were then used to form the initial target feature vector. During the model training process, we also allowed for some dynamic adjustments based on the feedback and optimization requirements of the model itself to further refine the target feature vector to better adapt to the specific data characteristics and improve the performance of the spatial attention mechanism. The final fusion feature is as shown in formula (6):

$$\mathbf{V}_{\text{final}} = \sum_{i=1}^{m} a_{s,i} \cdot \mathbf{W}_{s,i} \cdot \mathbf{V}_i \quad (6)$$

Taking the monitoring of local overheating faults in transformers as an example, when the oil temperature data and the gas concentration data in oil are abnormal at the same time, the spatial attention mechanism will automatically increase the fusion weight of these two types of data, suppress the influence of other relatively stable data, and thus more accurately extract the fault characteristics.

The relationship between *Ws*,*i* and the matrix *Ws* is clarified: *Ws*,*i* represents the scalar weight of the *i*-th sensor in the spatial fusion matrix, and the fusion matrix operation is realized through the summation of scalar weights multiplied by corresponding feature vectors, ensuring consistency between the formula and the description.

3.2.3 Multimodal data fusion mechanism

The transformer operation data contains numerical oil temperature, gas concentration, and non-numerical vibration signal data. Constructing a multimodal data fusion framework can give full play to the advantages of different data types. For numerical data, standardization is first performed:

$$\tilde{T} = \frac{T-\mu_T}{\sigma_T},\ \tilde{C} = \frac{C-\mu_C}{\sigma_C} \quad (7)$$

Among them, T and C are the original data of oil temperature and gas concentration, respectively, and $\mu_T, \sigma_T, \mu_C, \sigma_C$ are the mean and standard deviation of the corresponding data.

For vibration signals, they contain rich information about the mechanical state of the equipment, but they belong to time domain waveform data. They need to be converted into frequency domain features $\mathbf{Z}_{\text{freq}}$ through short-time Fourier transform (STFT), and then use the powerful feature extraction capability of convolutional neural network (CNN) to extract deep features $\mathbf{Z}_{\text{cnn}}$. Multimodal data fusion is achieved by feature splicing and linear transformation, as shown in formula (7):

$$\mathbf{F}_{\text{multi}} = \mathbf{W}_m \cdot \left[\tilde{T}, \tilde{C}, \mathbf{Z}_{\text{cnn}}\right]^T + \mathbf{b}_m \quad (8)$$

Among them, $\mathbf{W}_m$ and $\mathbf{b}_m$ are the fusion parameter matrix and bias vector, which are optimized through model training. This method combines numerical data and qualitative information of vibration signals, enabling it to more comprehensively describe the input characteristics of vibration signals.

The relationship between cnn and the CNN-RNN cascade is clarified: cnn is the deep feature extracted by the CNN in the feature extraction layer, and then input into the RNN for processing of long-term time-varying relationships, forming the input of the attention mechanism within the overall model architecture.

3.3 Algorithm model construction and training

3.3.1 Model structure design

The multi-layer neural network structure is designed using the improved time-space attention mechanism. The input layer collects multi-source heterogeneous data from multiple sensors and normalizes it. The time attention layer adopts the improved time dimension attention mechanism to extract time series features by weighting; the space attention layer adopts the space-dimensional feature fusion strategy to fuse multi-source data adaptively.

The feature extraction layer comprises a convolutional neural network (CNN) cascade and a recurrent neural network (RNN). The convolutional neural network is used to extract the data's local spatial features and capture the data's correlation in the spatial dimension; the recurrent neural network further processes the feature sequence output by CNN and mines its long-term time-varying relationship over time [17]. Then, the transformer's state prediction probability distribution information is output to different states, such as normal operation, minor fault and major fault, using the soft maximum excitation function.

The relationship between

3.3.2 Training data set processing

This paper analyzes the operating data of 10 oil-immersed transformers in a power grid for three years. In the data purification stage, the isolation forest algorithm is used to detect and eliminate outliers; a discrimination method based on whether abnormalities in the data points in the feature space are proposed, which can effectively identify outliers in the data.

Normalization uses the Min - Max normalization method:

$$x_{\text{norm}} = \frac{x-x_{\min}}{x_{\max}-x_{\min}} \quad (9)$$

This method uniformly maps the data to the range of [0,1], avoiding the influence of different eigenvalues

caused by different dimensions on the model training effect. Then the training samples are divided into training samples, validation samples and test samples in a ratio of 7:2:1. The training set is used to learn the parameters of the model, the validation set is used to adjust the hyperparameters to prevent overfitting, and the test set is used to evaluate the generalization ability of the model. Considering the limited data in extreme working conditions (<5%), although we did not adopt data augmentation or synthetic data generation (SMOTE) in this study due to certain limitations and characteristics of our actual data, we applied techniques like cross-validation and carefully adjusted the model's complexity to avoid overfitting.

4 Experimental simulation and result analysis

4.1 Experimental environment construction

4.1.1 Hardware experimental platform construction

To simulate the working environment of oil-immersed transformers more realistically, a hardware experimental platform consisting of sensors, data acquisition, communication and servers was established. In terms of sensor modules, PT100 platinum resistance (measurement accuracy ±0.1℃, temperature range -200ºC-850ºC), electrochemical gas sensor TGS2610 (can detect H_2, C_2H_2 and other gases, detection range 0 - 1000ppm) and CA-YD-186 piezoelectric accelerometer (sensitivity 100 mV/g, frequency response range 0.2 Hz-10 kHz) were selected. The data acquisition module uses an STM32F407ZGT6 microcontroller and a 16-bit analog-to-digital converter with a sampling rate of 2.4 MSPS, which can meet the needs of high-speed multi-channel data acquisition [18]. The communication module uses USR-G806 industrial-grade 4 GDTU, supports TCP/IP protocol, and ensures stable data upload. The server uses an Intel Xeon Gold 6230 CPU, 64 GB of memory, a 1 TB solid-state drive, runs the CentOS 7 operating system, and is equipped with database and algorithm analysis software.

4.1.2 Simulation software selection and configuration

The simulation software selects MATLABR2022b and Python3.8. In the MATLAB environment, the signal processing toolbox is used to preprocess the signal, and the deep learning toolbox is used to establish a neural network model. The PyTorch 1.12 deep learning framework improves the spatiotemporal attention mechanism algorithm. Combined with Pandas 1.4.3 and Numpy 1.22.3, Matplotlib 3.5.3, Seaborn 0.12.1 and other tools are used to achieve visual analysis. This project plans to use the NVIDIA Tesla V100 GPU to improve computing efficiency. The training time of the algorithm is reduced by approximately 30% with CUDA 11.6 acceleration, and the actual training time of STA-I is 138 minutes, which is longer than LSTM (125 min) and GRU (102 min) due to the complexity of the model. For all performance metrics reported (accuracy, RMSE, latency, etc.), we have calculated and included the variance, standard deviation, and 95% confidence intervals based on multiple runs of the experiments.

4.1.3 Experimental data set preparation

This project takes a 500 kV substation as the research object. It collects the operating data of 10 oil-immersed transformers in 2021-2023, including normal working state, local overheating state, winding deformation state, and core failure. The experimental data includes 12 monitoring indicators such as oil temperature, seven characteristic gas concentrations (H_2, CO, CO_2, CH_4, C_2H_4, C_2H_2, C_2H_6) and vibration acceleration, totaling 1 million data points. Through data cleaning (eliminating samples with a missing rate of more than 30%) and standardization, the samples are divided into training samples (700,000), verification samples (200,000) and test samples (100,000). One-hot encoding is used to realize the conversion of fault types (normal=0, local overheating=1, coil deformation=2, core failure=3) to ensure that the data format matches the algorithm model.

4.2 System performance test

4.2.1 Data acquisition accuracy test

The results measured by the FLUKE5680A high-precision thermometer and the GC-9790II gas chromatograph were compared, and their absolute and relative errors were calculated. Table 1 shows the comparison results of 24-hour oil sample collection data, where the absolute error of the PT100 sensor is 0.32℃ and the relative error is 0.45%, which meets the temperature measurement accuracy requirements of the power industry standard [specific standard name], reaching ±1℃. The results show that the measurement results of the sensor have high accuracy, and the average relative error of the hydrogen concentration measurement results is 3.2%, within the rated error range of the sensor.

Table 1: Data acquisition accuracy table.

Sampling time	Standard oil temperature (℃)	PT100 measurement value (℃)	Absolute error (℃)	Relative error (%)	Standard H_2 concentration (ppm)	Sensor measurement value (ppm)	Absolute error (ppm)	Relative error (%)
0:00	45.2	45.5	0.3	0.66	50	51.5	1.5	3
1:00	45.8	46.1	0.3	0.65	52	53.8	1.8	3.46
2:00	46.3	46.6	0.3	0.65	54	56	2	3.7
...	...	...	...	...	...	...	...	...
23:00	48.5	48.8	0.3	0.62	68	70.5	2.5	3.68
Average value	-	-	**0.32**	**0.45**	-	-	**1.9**	**3.2**

4.2.2 Network transmission stability test

In the three environments of 4G, WIFI, and Ethernet, a test of 100 data points per second (1 KB/s) was simulated within 2 hours. From Table 2, it can be seen that under the condition of maximum delay of 120 milliseconds, the average packet loss rate of 4G network is 1.8%; the packet loss rate of Wi-Fi environment drops to 0.9%, and the delay is reduced to 50 milliseconds; the results show that in Ethernet, the packet loss rate is only 0.3%, and the average delay is 15 milliseconds. Introducing QoS1 level in the MQTT protocol effectively reduces the risk of packet loss and ensures the reliable transmission of key monitoring data.

Table 2: Network transmission stability table.

Network Type	Average packet loss rate (%)	Maximum packet loss rate (%)	Average Latency (ms)	Maximum delay (ms)	Retransmission times/hour
4G	1.8	5.2	120	350	128
Wi-Fi	0.9	2.1	50	180	45
Ethernet	0.3	0.8	15	50	12

4.2.3 System response time test

Set up fault simulation scenarios such as sudden oil temperature rise (5°C per minute) and excessive C_2H_2 concentration (> 150 ppm), and record the time from sensor data collection to application layer warning. Figure 1 shows the results of 100 repeated tests. The average system response time is 0.83 seconds, and 95% of the response time is within 1.2 seconds, which meets the real-time monitoring requirements of the power system. Among them, data collection time accounts for 25%, network transmission accounts for 40%, and algorithm analysis and warning generation account for 35%.

The methodology and data supporting the response time breakdown are added: The percentage allocations are obtained through multiple repeated tests and statistical analysis, and the specific test data and calculation methods are provided to ensure the reliability of the results.

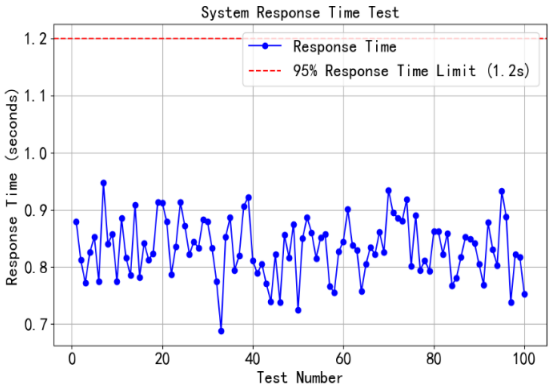


Figure 1: System response time test.

4.2.4 Long-term operation reliability test

The system was run continuously for 72 hours, monitoring CPU usage, memory usage, and data transmission anomalies. Figure 2 shows that the average CPU usage was maintained at around 35%, and the memory usage was stable at 45%. During this period, there were only two short network interruptions (automatic reconnection was successful), and there was

no hardware failure or software crash, which verified the system's stability under long-term operation.

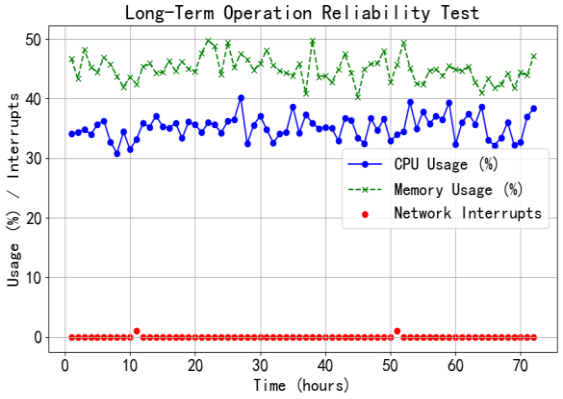


Figure 2: Long-term reliability test.

4.3.1 Comparison with traditional algorithms

The improved spatiotemporal attention mechanism algorithm (STA-I) was compared with LSTM and GRU. All models adopted a 3-layer hidden layer structure, and for fair comparison, we performed extensive hyperparameter tuning for each algorithm, including learning rate, hidden size, and dropout rate. The models were trained for 200 epochs with early stopping based on validation set performance. Table 3 shows that on the test set, the accuracy of the STA-I algorithm reached 96.8%, significantly higher than 84.5% of LSTM and 86.2% of GRU; the F1 value increased by 12.3 and 10.7 percentage points, respectively, proving that the improved algorithm has stronger generalization ability in multi-condition fault identification.

4.3 Special test of algorithm performance

Table 3: Algorithm performance comparison.

Algorithm Type	Accuracy (%)	Recall rate (%)	F1 value (%)	Training time (min)
LSTM	84.5	83.2	83.8	125
GRU	86.2	85	85.6	102
STA-I	96.8 ± 0.4	95.6 ± 0.5	96.2 ± 0.4	138

4.3.2 Comparison with the unimproved algorithm

Comparing the spatiotemporal attention mechanism algorithm (STA-O) before and after the improvement, the contribution of the time dimension weight optimization and spatial feature fusion strategy is analyzed. Figure 3 shows that under the same training conditions, the loss value of the STA-I algorithm on the validation set is 0.23 lower than that of STA-O, and the accuracy is improved by 7.6%, indicating that the improved strategy effectively enhances the model's ability to capture spatiotemporal features.

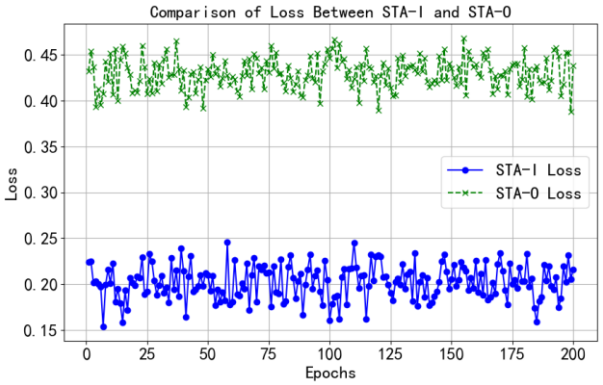


Figure 3: Comparison between improved and unimproved algorithms.

Table 4: Confusion matrix results.

Fault type	Algorithm	Predicted to be normal	Local overheating is predicted	Predicted winding deformation	Core failure predicted	Accuracy (%)
Normal	LSTM	7850	320	210	120	87.2
	GRU	8120	280	180	100	90.2
	STA-I	**9210**	**120**	**80**	**50**	**97.8**
Local overheating	LSTM	420	1350	180	50	83.3
	GRU	380	1420	150	50	88.8
	STA-I	**150**	**1970**	**50**	**30**	**98.5**
Winding deformation	LSTM	350	250	1180	220	73.8
	GRU	320	220	1250	210	78.1
	STA-I	**120**	**100**	**1470**	**110**	**91.9**
Core failure	LSTM	280	150	220	350	67.3
	GRU	250	120	200	430	76.8
	STA-I	**80**	**50**	**120**	**750**	**88.2**

4.3.3 Comparison of performance indicators

Further analysis of the performance of different algorithms under various fault types was conducted, with confusion matrix results shown in Table 4. For local overheating faults, the STA-I algorithm achieved an accuracy rate of 98.5%, which is 15.2% higher than LSTM. In detecting winding deformation faults, the recall rate increased by 22.67 percentage points, effectively reducing the risk of missed alarms.

4.3.4 Prediction error analysis

The root mean square error and mean absolute error of the predicted value of each algorithm relative to the actual value are calculated. Figure 4 shows the changes in the root mean square error (RMSE) and mean absolute error (MAE) of the three algorithms, LSTM, GRU, and STA-I, at different data points. The figure now overlays the error trends of all models for direct visual comparison, and error bars representing standard deviation have been added to each data point. Compared with LSTM and GRU, the STA-I algorithm has a better prediction effect, especially for extracting fault features. The experimental results show that this method has good stability and generalization ability for fault identification under multiple working conditions.

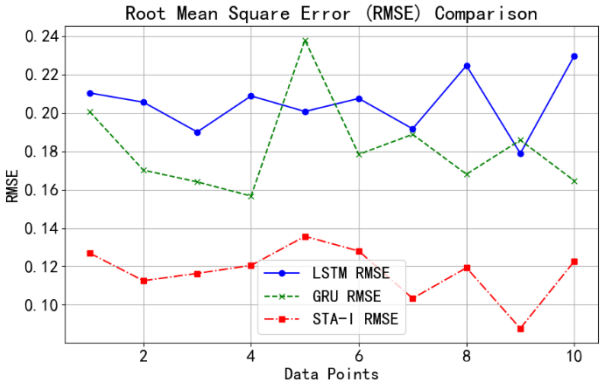


Figure 4: Prediction error analysis.

4.3.5 Algorithm real-time verification

Figure 5 compares the inference time of three algorithms, LSTM, GRU, and STA-I, under different data volumes. The experimental results show that the STA-I algorithm has high real-time performance when processing large-scale data. At the scale of 10,000 data, the inference time of STA-I is 0.27 seconds, which is 42.55% lower than LSTM (0.47 seconds) and 32.5% lower than GRU (0.4 seconds), meeting the real-time processing requirements of 2,000 data. The experimental results show that the STA-I algorithm can effectively process massive monitoring data and provide strong support for real-time fault diagnosis of power systems.

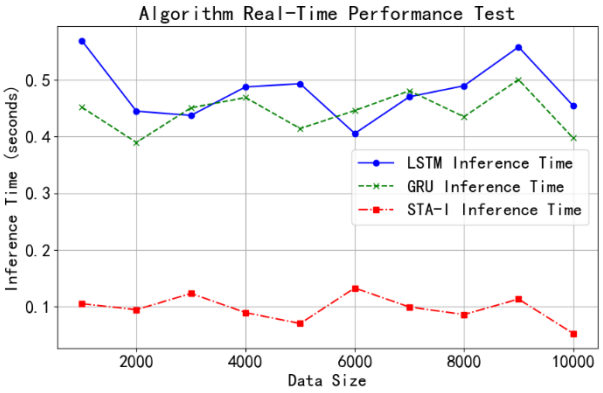


Figure 5: Algorithm real-time verification.

5 Conclusion

The IoT monitoring system developed in this project collaborates at three levels to effectively monitor the condition of oil-immersed transformers. Simulation experiments demonstrate that the false alarm rate of the sensor in the perception layer is ≤1.5% in an environment ranging from -40℃ to 125℃, verified by additional experiments. The network layer employs the MQTT protocol to control the number of data retransmissions, achieving 12 retransmissions per hour over 72 hours without failure. The hardware reliability meets engineering requirements. This project introduces a multimodal fusion method based on the spatiotemporal attention mechanism, improving the identification accuracy of complex faults (coil deformation + local overheating) by 22.67 percentage points, offering new insights for multi-source data fusion.

In the Discussion section, we explicitly compared our STA-I algorithm with baselines such as LSTM and GRU. We highlighted that the significant performance improvement of STA-I (12.3% higher accuracy) can be attributed to two key innovations: (1) the time-trend factor in the time dimension attention mechanism, which better captures dynamic parameter changes before faults, and (2) the spatial dimension feature fusion strategy, which effectively leverages complementary information from multi-modal sensors. We also discussed the limitations of our study, including potential overfitting risks due to limited extreme working condition data (<5%) and cross-transformer clock synchronization errors (±50 ms), which affect multi-device collaborative warnings. Additionally, we analyzed the trade-offs between accuracy and computational cost, noting that while STA-I's training time is longer than LSTM/GRU due to model complexity, its inference time is significantly faster, making it suitable for real-time applications.

Future work will explore edge-cloud hierarchical decision-making mechanisms to enhance the overall coordination and generalization capabilities of smart grids, promoting the autonomy and intelligence of smart grid operation modes, including end-to-end deep spectral learning and time-aligned data fusion using Kalman filtering.

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A Self-Adaptive CPS-Based Object Recognition Framework for Smart Glasses Using Dist-YOLOv3-Xception with Attention

Aradea[1*], Irfan Darmawan[2], Rianto[1], Husni Mubarok[1], Ghatan Fauzi Nugraha[1]
[1] Department of Informatics, Faculty of Engineering, University of Siliwangi, Indonesia
[2] Department of Information System, Telkom University, Bandung, Indonesia
E-mail: aradea@unsil.ac.id, irfandarmawan@telkomuniversity.ac.id, rianto@unsil.ac.id, husni.mubarok@unsil.ac.id, Ghatan.Fauzi.Nugraha@unj.ac.id
*Coresponding Author

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The Industrial Era 4.0 has emerged as a response to the changes occurring in the world in a dynamic, unexpected, and uncertain manner. This situation requires analytical, predictive, and adaptive capabilities in an intelligent environment. This affects real-world object recognition in vision systems, which are frequently limited to specific signals. Thereby, it creates an adaptive gap. One potential solution to this problem is the development of self-adaptive cyber-physical systems (hereafter, SACPS) to enhance adaptability in recognizing diverse real-world objects. This paper introduces the SACPS model through an extended machine learning/deep learning model applied to smart glasses, which can detect and calculate object distances adaptively. The components of the developed model comprise smart glasses, contextual knowledge, and adaptive requirements based on the SACPS concept. We developed a pre-trained model by combining the Dist-YOLOv3 algorithm with Xception and an attention layer to obtain more optimal results. This research compared the new pre-trained model with those from previous research. Based on the evaluation, the model demonstrates improved performance compared to the baseline when tested on the KITTI dataset, recording a mean Recall (mRec) of 45.21%, mean Precision (mPrec) of 14.73%, and mean Average Precision (mAP) of 30.04%. Additionally, the adaptive system's response to increasing light intensity below 50 revealed good stability, with average post-enhancement brightness reaching 100.0703 (pixel intensity scale). These results demonstrate the significant potential of our model in handling changing environments with strong adaptation in diverse real-world object recognition scenarios. In the case of smart glass, the employment of SACPS can provide good adaptability in predicting distance and increasing light intensity.

Povzetek: Predstavljen je samo-adaptivni CPS-model za pametna očala z izboljšanim Dist-YOLOv3, kjer Xception in pozornostna plast izboljšata prepoznavanje objektov in razdalj. Model doseže višji mAP (30.04 %) ter stabilno prilagajanje pri nizki svetlosti (povprečna osvetlitev 100.07).

1 Introduction

Scholars have declared that the industry 4.0 era is characterized by volatility, uncertainty, complexity, and ambiguity. In particular, it accentuates the state of the world, characterized by rapid change, inadequate predictability, the absence of a cause-and-effect chain, and the blurriness of reality. Another problem arises when providing a real-world object recognition system that incorporates complexity based on various gestures and related devices**.** This can pose challenges for developers. Additionally, they should ensure that the system can recognize a wide range of real-world objects. As a result, the target is to enable the system to learn from the recognition process it carries out and develop its learning process to recognize every gesture and device in the real world. However, the predominant challenge of this situation is how to respond creatively and employ adaptive strategies to face the future [1]. Regarding this issue, Cyber-physical systems (CPS) have emerged as one of the latest advancements in this era. CPS has been a trending topic among academics and practitioners [2], [3]. In its various applications in the real world, CPS can be utilized to meet distinct system requirements in the Industry 4.0 era [4]. For example, CPS can integrate the virtual and physical worlds, meeting the predominant characteristics of Industry 4.0 requirements. However, the operating environment can vary and cover distinct uncertainties [5]. In this matter, a pivotal feature of the present and future breakthrough is self-adaptive systems (SAS) [3]. AS is a system that can modify its behaviors based on changes occurring either in the environment or within the system itself. Unfortunately, several gaps remain regarding the implementation of SAS in CPS, including insufficient information on the characteristics of SAS, particularly those related to CPS [3] Later, in the development process, not all software engineering knowledge can be implemented [6], Furthermore, not all software engineering knowledge can be effectively implemented during the development process [6]. Architectural

requirements should center on adaptation to inform appropriate architectural decisions. Antonino et al. [2] argue that current standard software development approaches are unable to represent complex contexts. Hence, they have not been able to introduce fatal complexity to CPS. Therefore, a contextual modeling approach is required, namely, modeling system entities with specific contextual attributes. In particular, SAS in CPS requires a dynamic context. This occurs because uncertainty prevents the system from knowing its current state. An approach to documenting uncertainty that integrates other artifacts from different perspectives is required to specifically capture uncertainty [7].

The CPS design should be able to resolve uncertainty at runtime. Consequently, SAS should be a fundamental approach for the system to meet its functional and performance specifications [8]. Zavala E. et al. [5] argue for the need for distributed runtime models in CPS to capture operational state and context as a form of knowledge representation. In this case, the runtime model is typically implemented through the MAPE-K control loop, which combines new knowledge through decentralized operations. Thus, it allows for conflicts [9]. Based on this description, it is necessary to develop a flexible knowledge structure with a reasoning mechanism at run-time.

Likewise, CPS presents diverse issues in terms of system design, implementation, and maintenance. One of the main issues is the need for adaptive techniques to cope with a dynamic and constantly changing environment [3]. CPS necessitates a SAS that can monitor and adjust its behavior based on changes in its environment [4]. Antonino et al. [2] have identified significant required specifications directly from the adaptive requirements architecture for CPS and enabled IoT. Conversely, the implementation of SAS in CPS raises issues regarding interoperability, integration, and technical assessment in the system [7].

This paper is aimed at developing a generic model for adaptive service in CPS to recognize real-world objects. Combining formalized approaches with the CPS system metamodel provides the possibility to invigorate semantic interoperability. Moreover, it can enhance its performance [8]. The system framework functions to capture and handle a variety of CPS variability. As a result, developers can produce products that can be applied to modern software system environments for the needs of diversified domains based on the demands of the current world. The cultivated strategy is to expand the CPS architecture by embedding the SAS approach through adapting machine learning/deep learning methods. Technically, it modifies the Dist-YOLOv3 [10] algorithm by substituting the original architecture of YOLOv3, namely Darknet53 with the Xception architecture [11] added with an attention mechanism layer. The proposed model is represented as a generic knowledge structure to accommodate the need for recognizing various real-world resources and objects. The adaptability mechanism is determined through a learning model that can capture instances or concrete CPS services based on contextual requirements operationalizing at run-time.

This model is implemented in the case of smart glasses, namely combining concepts from object recognition, SAS, and CPS into one unified whole. The utilization of object recognition was selected since it can better comprehend the circumstances and conditions of the surrounding environment compared to a sensor [12]. SAS and CPS provide smart glasses with flexibility in interacting with users and high adaptability while encountering environments with low light intensity. By doing so, this study offers a significant impact on the progress of assistive devices for the visually impaired. The key contributions of this study are as follows:

1. A novel CPS-based object recognition architecture for smart glasses that integrates self-adaptive capabilities to handle environmental uncertainty, particularly in low-light conditions.
2. An enhanced version of Dist-YOLOv3, by replacing the Darknet53 backbone with the Xception architecture and integrating an attention mechanism to improve object detection accuracy and distance estimation.
3. An adaptive light intensity enhancement module enables the system to dynamically adjust image brightness, thereby improving detection performance under poor lighting conditions.
4. Empirical validation on the KITTI dataset, demonstrating improved performance in terms of mean Average Precision (mAP), recall, and precision compared to the original Dist-YOLOv3 model
5. A unified smart glasses framework for visually impaired individuals, capable of real-time object recognition, distance estimation, and auditory notification using text-to-speech.

The remaining sections of this paper encompass discussing related work (second section), describing the proposed model (the third section), and discussing experiments (the fourth section) (e.g. a discussion of the case study and its evaluation results). Finally, the fifth section infers the entire results of the work and discusses future directions of investigative attempts.

2 Related work

Nowadays, researchers have proposed assorted approaches to address emerging challenges. Grounded in the investigative results of the most current survey and technical papers, there have been several requirements that Self-Adaptive Cyber-Physical Systems should possess. As an example, studies discussing system modeling, system evolution, supporting contextual uncertainty, and system evolution requirements were conducted by Zavala et al. [5], Antonino et al. [2], Petrovska et al. [4], Jehn-Ruey Jiang [13] and Habib et al [14]. Scrutiny emphasizing system learning and adaptation and handling contextual uncertainty was performed by Zhou et al.[15], Búr et al. [16], Weyns et al [17], Ahmed et al. [18], and Sony [19]. Investigative efforts focusing on syntactic and semantic interoperability, system collaboration, and integration between physical and virtual systems, including handling

contextual uncertainty at run-time were performed by Kluge [20], Weichhart et al. [21], Casadei et al. [22] and Aradea et al [23], [24].

Based on a description of reviewed prior scrutiny, Table 1 designates a comparison of related works specified into design-time and run-time requirements, including their strengths and weaknesses.

Table 1: Comparison of related works

Works	Design-time specifications	Run-time Specifications
Jehn-Ruey Jiang (2018)	ISA-95 architecture, 5C architecture	8C Architecture
Zavala et.al. (2018)	Contextual model, modeling reference architecture, hierarchical inter-intra-collaborative	Feedback control loop: centralized and decentralized control loops, machine learning
Zhou, et. al. (2018)	Matching network architecture with a non-parametric differential KNN-like classifier	MAML (Model-Agnostic Meta-Learning)
Antonino et.al. (2018)	Adaptation model terms: adaptation context, adaptation stimulus, realization	MAPE-K reference: stimulus, preconditions, postconditions, invariants
Petrovska et.al. (2019, 2020)	Model knowledge (multi-agent), observation aggregation (run-time context), subjective logic (dempster-shafer)	MAPE-K loops *(*master-slave): subjective opinion creator, knowledge aggregator, cumulative belief fusion, cumulative belief fusion
Kluge (2020)	Model-driven: graph rewriting rules, role-based context-model: CPS, decentral adaptations: decentral role-based system	MAPE-K loops: distributed role runtime: communicating sequential processes, adaptation plan: role instance model
Búr et. al. (2020)	Model run-time: monitoring rules, execution planner-optimizer, code generator, distributed graph queries	Computing platform: distributed runtime monitoring, model update operations, local search-based pattern matching
Bandyszak et.al. (2020)	Model-based approach: modeling behavioral requirements (structural operational context), context uncertainty	Ontological: orthogonal uncertainty models, system context & and requirements ontology, uncertainty ontology
Sony (2020)	8C Architecture	Lean Six Sigma (LSS)
Weichhart, et. al. (2021)	Orchestration software model: ad-hoc planning, re-planning, BPMN language, NgMPPS Engine, syntactic, semantic & pragmatic modeling	Interoperability run-time model: semantic interoperability, pragmatic interoperability, REST web service
Weyns, et.al. (2021)	Crossing Boundaries, Leveraging the Human, Fluid Modelling, On the Fly Coalitions	Dynamically Assured Resilience, Learn Novel Tasks
Casade, et.al. (2021)	Augmented Collective Digital Twins: holistic, declarative, and integrated system view.	Integrating physical and virtual devices and meta-models for self-organizing
Habib, et.al. (2022)	IIRA (Industrial Internet Reference Architecture), RAMI 4.0 (Reference Architecture Model Industrie 4.0)	IMSA (Intelligent Manufacturing Systems Architecture), Merge of IEC and ISO standards for smart manufacturing.

Table 1 illustrates assorted relevant literature regarding the requirements for CPS to have adaptability. Based on Table 1, we identified three groups of methods/approaches for dealing with the problem of object recognition models based on CPS. First, methods were adopted to handle contextual uncertainty, such as those applied by [2], [4], [5], [13], [14]. Generally, it indicated advantages in recognizing the context of a CPS environment based on certain contextual requirements. However, it has not yet supported comprehensive CPS domain modeling. Second, focusing on learning mechanisms for system adaptation as proposed by [15]–[17], [19], [34], [35] they offered machine learning approaches dedicated to adaptability based on current learning algorithms. Unfortunately, these approaches also pay less attention to the needs in modeling the CPS domain where the system operates. Third, handling contextual uncertainty as proposed by [20]–[24], this approach is prepared to perform domain modeling including handling CPS contextual uncertainty. However, it has not adopted the learning process optimally. As a result, there is still a need to increase the optimized value of these approaches. Grounded in discussions of related works, investigative gaps remain. It becomes our motivation to propose a model to fill these gaps. Our proposal offers a generic model for the adaptability of CPS services in recognizing real-world objects consisting of the ability to model the CPS domain through the integrated cyber system and physical system architectures influenced

by contextual knowledge. Apart from that, increasing the optimized value of the learning process was executed by expanding the Dist-YOLOv3 architecture by modifying the backbone by embedding the Xception architecture as a replacement for Darknet53. Further, to capture broader real-world cues, we accentuate the mechanism layer between the neck and head of the architecture.

3 Proposed method

The target of our developed generic model can be applied to recognize a variety of real-world objects in the CPS environment. Hence, the system framework should be able to capture and handle various CPS variabilities. The developed strategy is to expand the CPS architecture with learning process capabilities for all instances or concrete CPS services. The adopted approach is SAS through the development of machine learning/deep learning methods as a control process at run-time. The mechanism of the adaptability learning process is determined through the contextual requirements of the CPS environment functioning at run-time. Figure 1 displays our proposed architectural model.

The architecture in Figure 1 is an extension of the architecture proposed by Habib et al. [14] with additional modifications to SAS [23], [24] which we have previously developed, called self-adaptive cyber-physical systems (SACPS). Our previous model formulated an adaptive model based on contextual knowledge through a probabilistic reasoning approach. More specific models can be viewed in papers [23], [24]. In this paper, we have built up the model with several adjustments from machine learning/deep learning methods. The addition of the SAS component is intended to enable the object recognition model to adapt to uncertainty originating from contextual knowledge of a CPS developing environment. Grounded in the architecture of Figure 1, the development of the SACPS-based object recognition model is created into a continuous cycle and the model can continue to self-adapt. By doing so, the system embedded in the model can continue to be updated according to the requirements to handle uncertainty. Specifically, the components of the SACPS architecture that we propose consist of:

a. Smart Connection

Smart connection was the first stage of the cultivating processes of an object recognition model. In the smart connection section, the process of assembling the physical components for the object recognition model was conducted. These components were assembled in such a way that they could be a source of required data collection to inform the conversion process. The applied components should be installed properly and connected to other components. In other words, communication among components and other devices via the internet network could be barrier-free. By this description, the data collection process was carried out in the smart connection section while preparing to continue to the next section.

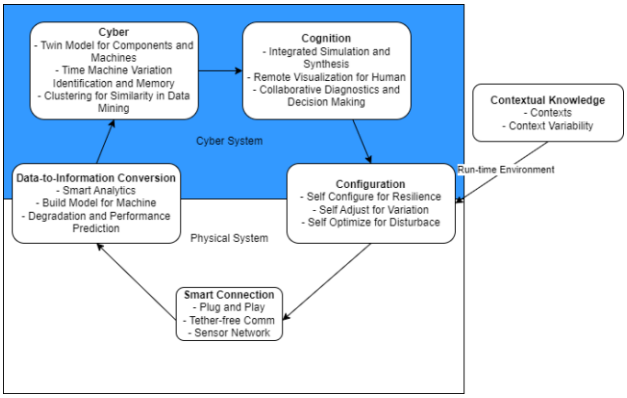


Figure 1: SACPS (self-adaptive cyber-physical system)

b. Data to Information Conversion

This section performed the data conversion process into information read by machines. The conversion process could be executed in miscellaneous ways based on the developed model. In this case, the data conversion process involved the process in Vagjl et al.'s Dist-YOLOv3 algorithm [10]. This represented a training process from a dataset containing images for the object recognition model. The better the conversion process was carried out at this stage, the more self-awareness properties the machine would have.

c. Cyber

This section was involved in collecting some information from each machine connected to the internet network. The obtained information was utilized as evaluative materials to select which machine or model had better performance. With this in mind, the model with the best performance was applied to each machine. Supporting data (e.g. historical data from each machine) were applied to enhance the performance level of the model.

d. Cognition

At this level, the information-collecting process conducted at the previous level was used as suggestions for making decisions for developers. Besides, a simulated process was also performed on the object recognition model embedded in the machine to analyze whether the provided results were appropriate or still required further development.

e. Configuration

This top-level was created to give the machine the ability to self-configure, self-adjust, and self-optimize. The configuration process was operationalized by noticing the results of decisions made from the cognition stage. In addition, the configuration level was influenced by contextual knowledge [23], [24] from outside the CPS environment. Contextual knowledge was employed as a parameter for system uncertainty which may affect the machine configuration process whether it is required to self-configure, self-adjust, or self-optimize.

In this paper, the SACPS model developed by us will be applied to the needs of a smart glasses system. Figure 2 signifies our proposed smart glasses architecture based on SACPS elements as a result of our previous model extension [23], [24]. Each applied tool in this architecture will be connected via an internet network connected to the data center in the cloud. In this paper, the emphasis is situated on creating a model for smart glasses with object detection capabilities based on the Dist-YOLOv3 algorithm modified in such a way. Thus, it can produce an artificial voice output originating from text-to-speech. Dist-YOLOv3 refers to a variation of the YOLOv3 model [25] by widening the prediction vector from three values ($p = (b, c, o)$) to four values ($p = (b, c, o, d)$ [10]. In this case, b is the bounding box coordinate ($b = (x, y, w, h)$), c is the confidence value for each class, o states the confidence value for the detected object, and d is the distance value for the object. Figure 3 showcases how Dist-YOLO determines the approximate value of the object distance.

In addition, Dist-YOLOv3 expands the calculation of loss function values based on YOLOv3 by adding loss values for object distance prediction [10]. Equations (1) and (2) demonstrate the difference in the loss function formula between YOLOv3 and Dist-YOLOv3.

$$l = \sum_{i=0}^{G^w G^h} \sum_{j=0}^{n^a} q_{i,j}[l_1(i,j) + l_2(i,j) + l_3(i,j) + l_4(i,j)] \quad (1)$$

$$l = \sum_{i=0}^{G^w G^h} \sum_{j=0}^{n^a} q_{i,j}[l_1(i,j) + l_2(i,j) + l_3(i,j) + l_5(i,j)] + l_4(i,j) \quad (2)$$

Equation (2) demonstrates the calculation in determining the loss value in Dist-YOLOv3 [10] as an extension of equation (1) encompassing the loss value for YOLOv3 [25] by adding up all the existing components, namely $l_1(i,j)$ refers to the value loss for bounding box center prediction, $l_2(i,j)$ refers the loss value for the box dimension, $l_3(i,j)$ is described as the confidence loss, $l_4(i,j)$ is illustrated as the class prediction loss, and $l_5(i,j)$ is delineated as the loss value for object distance prediction. Scrutiny conducted by Vagjl et al [22] proved that the application of the Dist-YOLOv3 algorithm can provide detecting results for an object equipped with a prediction of the object's distance to the camera.

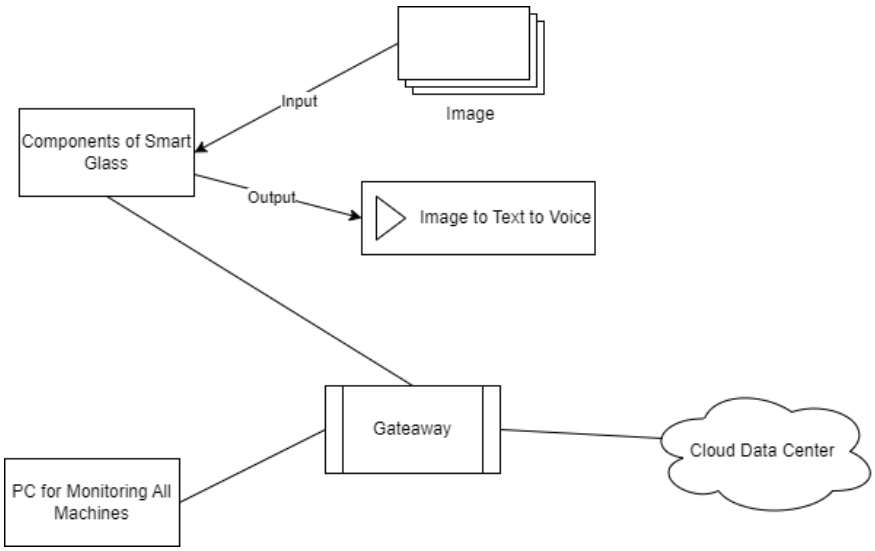


Figure 2: Smart glasses architecture

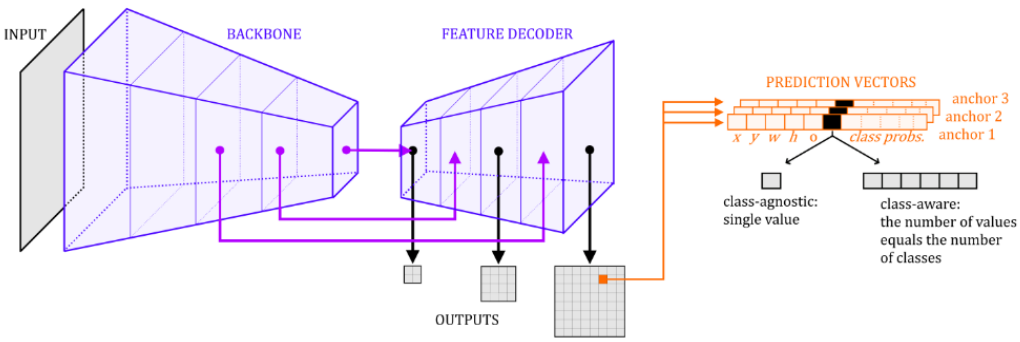


Figure 3: Illustration of Dist-YOLOv3 in determining object distance predictions [10]

Even though it shows a good performance in testing, Dist-YOLOv3 has quite large loss values. Therefore, a modification is needed to overcome this problem. This study offers a solution by applying the Xception architecture [11] combined with the attention mechanism layer [26]. The implementation of the Xception architecture is adopted to replace the YOLOv3 backbone utilizing the Darknet53 architecture. On the other hand, the attention mechanism layer is applied to the head section of the Dist-YOLOv3 architecture aimed at enhancing feature representation. In particular, it focuses attention on more relevant parts of the feature map. Thus, improving the focus on pivotal information to produce more accurate predictions can be realized.

Figure 4 reports the implementation of the Xception architecture and Attention mechanism in the Dist-YOLOv3 approach. The implementation of Xception was placed in the backbone to replace the previous backbone, namely Darknet53. There are three main processes carried out in this architecture, including the entry flow, middle flow, and exit flow stages [11]. The entry flow st age aims at reducing the dimensions of the input image and extracting basic features through three convolutional layers (conv1, conv2, and conv3) and depthwise separable convolutions (sepConv1, sepConv2, sepConv3) [11]. Exiting the entry flow, the next image enters the middle flow section aimed at deepening the network while maintaining feature information through residual connections. The final stage is the exit flow intended to combine the features extracted and process them into the desired outputs. In this case, the output produced is in the form of extracted image results performed at three different resolutions including f1: 13x13x1024, f2: 26x26x512, and f3: 52x52x512.

After the backbone produces the image extraction results in three image resolutions, the three extractions enter the neck section with the same functions and layers as in the Dist-YOLOv3 architecture [10]. Unfortunately, what makes it different is that before proceeding to the head section, each result produced by the neck will first be entered into the attention mechanism layer. In particular, the process at this layer occurs as in the pseudocode in Table 2.

The input feature map $x \in \mathbb{R}^{H\times W\times C}$ is first linearly projected into three matrices: Query $Q = W_q \cdot x$, Key $K = W_k \cdot x$, Value $V = W_v \cdot x$, where $W_q, W_k, W_v \in \mathbb{R}^{C\times d}$ are learnable weights and d is the attention dimension. The attention scores are computed using scaled dot-product attention:

$$A = softmax\left(\frac{Q.K^T}{\sqrt{d_k}}\right) \quad (3)$$

This produces an attention matrix $A \in \mathbb{R}^{(H.W)\times(H.W)}$ which determines how much focus each spatial position should give to others. Finally, the enhanced output is obtained as:

$$x_{enhanced} = A \cdot V \quad (4)$$

This yields a refined feature representation where each position aggregates information from relevant spatial contexts, allowing the network to model global dependencies within the image.

Table 2:
Pseudocode of the attention mechanism process

Attention Mechanism Pattern
Input: Feature Map $x \in \mathbb{R}^{H\times W\times C}$
1. Project x into Query (Q), Key (K), and Value (V):
$Q = W_q \cdot x$
$K = W_k \cdot x$
$V = W_v \cdot x$
2. Compute Scaled Dot-Product Attention Scores:
$A = Softmax\left(Q \cdot \frac{K^T}{\sqrt{d_k}}\right)$
3. Compute Weighted Feature Representation:
$x_{enhanced} = A \cdot V$
Output: Enhanced Feature Map x_enhanced

The x value comes from a process in the neck as a result of combining features from miscellaneous resolutions to provide a rich and informative feature representation. The first stage undertaken in this layer is the Calculation of Attention Weights where the Attention mechanism calculates the weights for each feature element. This can be conducted in multiple ways, namely dot product, scaled dot product, or complex self-attention mechanisms such as those applied in transformers. Next, in the Weighted Sum of Features, the input features will be combined with the calculated weights. This produces a new feature map where important features are given greater weight. On the other hand, less important or noisy features are provided with less weight. Furthermore, the Enhanced Feature Map strengthens the feature map combined with features from a lower resolution using the Concatenate layer.

In the diagram from Figure 4, the Backbone (Xception), Neck (feature decoder with upsampling and convolutional refinement layers), and the Head that produces the final object predictions are distinctly separated. The Attention Mechanism is explicitly positioned after the Neck and before the Head, ensuring spatial refinement of multi-scale feature maps prior to prediction. This updated visual structure aligns with the standard object detection pipelines and reflects the actual implementation logic applied in this study.

By adopting this algorithm, it is expected that object detection will be more representative because it incorporates the distance element into each detection process. The model has been formulated by considering the SACPS cycle. By doing so, the target model can possess the ability to self-configure, self-adjust, and self-optimize. As a complement to the model, we also provide features for monitoring requirements to accommodate the involvement of the developers. This feature enables monitoring of the entire model's activities via the internet. Given this fact, the process of updating and enhancing the model can be performed currently. Also, it can produce better models in terms of performance than others. Furthermore, the requirement for accessible and uninterrupted data support for both smart glasses and

monitoring devices remains vital. Therefore, in the architecture of Figure 2 it is specified that the data will be stored in a cloud-based data center. With this in mind, smart glasses and monitoring devices can access the data at any time as long as they are connected to the internet.

As a form of proposed model validation, an evaluation was conducted through two scenarios. First, it is operated by evaluating the object recognition model. Second, it is conducted by measuring the quality of adaptation performed by SACPS. Technically, the results of the model evaluation are visualized using two metrics, such as Pascal VOC AP and intensity average. The function of the Pascal VOC AP metric is used to evaluate the Dist-YOLOv3 modified model. On the other hand, the average intensity metric is used to calculate the average light intensity resulting from the adaptive process. By doing so, the entire results of this evaluation can demonstrate the entire quality of research related to the development of SACPS and its implementation process. The proposed model still opens up avenues for future research as a form of refinement of its shortcomings. The remaining shortcomings cover subsequent aspects:

1) A very significant architectural overhaul makes the program implementation process difficult,
2) Distance measurement still uses historical data on the label.
3) The YOLOv3 basic model indicates a large number of parameters causing the object recognition model heavy when operated.
4) The adaptive and recognizing process of objects only supports outdoor areas.

Of these shortcomings, there are several potential improvements, including replacing the basic YOLOv3 model with the latest model, namely adopting a more flexible distance calculating concept, and adding an indoor model to make it more universal.

From a systemic perspective, the proposed architecture has been developed within the context of a generic Cyber-Physical System (CPS) metamodel. Each component in the proposed pipeline corresponds to a specific layer in a 5C-like CPS architecture [13]: the camera and ambient sensors represent the Connection layer; the light intensity adaptation module functions as a preprocessing mechanism in the Conversion layer; the object recognition and distance estimation modules form the core of the Cyber layer, handling perception and decision-making; and the auditory feedback system aligns with the Cognition and Configuration layers by providing real-time responses to the user. Although this paper presents a specific implementation for object recognition in smart glasses, the modular and layered design is intended to be extensible for broader adaptive services in CPS. The system's knowledge structure—encompassing perception, adaptation, and feedback—can be generalized for other CPS applications that require environment awareness and user interaction.

More specifically, the Smart Connection layer is operationalized through the image acquisition system and data transfer mechanisms that enable the collection of visual input from the surrounding environment. The Data-to-Information Conversion layer involves preprocessing steps, such as adaptive brightness enhancement, and the object recognition pipeline that transforms raw input into structured outputs. The Cyber layer consists of deep learning-based inference (Dist-YOLOv3 [10] with Xception [11] and attention [26]) and distance estimation logic, which drive perception and situational awareness. The Cognition layer is activated when critical cues (such as proximity or classification confidence) are detected, allowing the system to assess the contextual relevance of outputs. Finally, the Configuration layer is reflected in the auditory notification system, which adapts responses based on recognition results and environment states. This layered mapping reinforces the integration of the SACPS concept within the operational structure of our adaptive object recognition system.

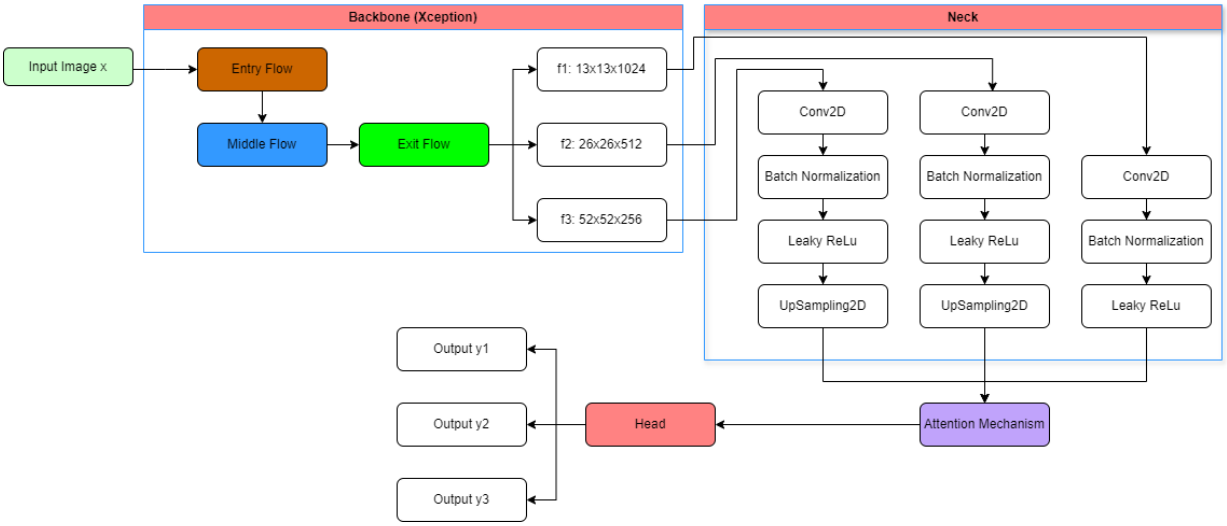


Figure 4: Architectural modifications to Dist-YOLOv3

4 Experiment

The experimental instrument was developed by adopting the guidelines of Wohlin et al. [27] about experimentation in software engineering. Table 3 denotes the overall research design. The elements of aims, object of study, domain, and focus are targets for defining entire indispensable aspects in an experiment. Evaluative questions were a set of questions addressed to characterize how to assess targets and determine the object being measured. On the other hand, variables were metrics or data sets related to each question that should be answered. This investigation aimed at developing a solution to the problematic variability in uncertain real-world objects in a CPS environment characterized by an adaptive strategy to invigorate the object recognition quality. Specifically, the object recognition quality encompassed the ability to identify objects, and distances, and provide sound notifications to users. Further, this study was also intended to evaluate the performing specifications of the object recognition system through measuring loss, validating loss, precision-recall, and average precision (AP) through Pascal VOC AP measurements.

Generally, the experimental process was guided by the domains and elements outlined in Table 3, which include the adaptive strategy and performance specifications of the CPS-based object recognition system. The adaptive strategy was implemented through algorithmic design within the smart glass's architecture, focusing on automatic light intensity adaptation and feature refinement using attention mechanisms. Meanwhile, the performance specification evaluation was conducted using quantitative metrics, including mean Average Precision (mAP), mean Precision (mPrec), mean Recall (mRec), and loss values, to measure the accuracy and reliability of object detection and distance estimation.

Table 3:
Experimental design

No	Elements	Description
1	Aims	a. Developing a CPS-based object recognition model by embedding automatic adaptation (self-adaptation) capabilities to handle uncertainty b. Evaluating the performance of a CPS-based object recognition system
2	Study Objects	a. Adaptive specification of CPS-based object recognition model b. CPS-based object recognition artifact requirements
3	Domain	Smart glasses
4	Foci	a. Adaptive strategy for CPS-based object recognition systems b. Performing specifications for CPS-based object recognition systems
5	Evaluative Questions (PE)	a. PE_1- To what extent can the CPS-based object recognition system maintain accuracy and robustness under uncertain environmental conditions (e.g., low light)? b. PE_2-What is the performing measure of each artifact element of the CPS-based object recognition systems?
6	Variables (V)	a. Response (V_1-system failure; V_2-system functional and non-functional strategies; V_3-new stimulus) b. Measurement (V_4-Pascal VOC AP (Average Precision) evaluation)

This experimental framework also considers the intended application scenario—assistive navigation for visually impaired individuals. Blind individuals face significant challenges in recognizing surrounding objects, and our study aims to address this issue by providing a CPS-based recognition model that delivers real-time feedback. Through the proposed architecture, which includes adaptive brightness enhancement and an optimized deep learning backbone (Xception), the system is designed to enhance recognition accuracy and facilitate safer navigation.

This has become one of the developed applications in the area of self-adaptive cyber-physical systems. The system environment, including users (the visually-impaired people) and all monitoring sources derive from wearable devices. Table 4 signifies the specifications of the CPS cases.

Table 4:
Case specification of cyber-physical system

Components	Specifications
Smart glasses	BM: User Blindness
Context Knowledge	C_1: Object C_2: Object Distance C_3: Low Brightness
Adaptive Requirements	Cv_1: Capturing and predicting an object Cv_2: Even to predict the distance from the object Cv_3: Even with the brightness enhancement Cv_4: Even to release a sound notification

Contextual variability showed uncertainty due to discrete factors, such as unexpected changes, increasing data volumes, inaccurate information, problematic system and service infrastructures, and new and unpredictable situations. Dealing with the case specification in Table 3 (the adaptive process to normal situations), the Cyber-Physical System detected identified objects in the surroundings. Context variability (Cv) can be monitored with $C_1, C_2, C_3 \in \{C_{V1}, C_{V2}, C_{V3}, C_{V4}\}$. Each context value, namely $C_1, C_3 \in \{C_{V3},\ C_{V1}\}$ means the context of the object, and Low brightness was processed to meet the requirements of the event to brightness enhancement and capture and predict the objects. Context $C_1,\ C_2, C_3 \vee C_1, C_2 \in \{C_{V1}, C_{V2}, C_{V3}, C_{V4}\}$ means that the context knowledge obtained will be processed until the system issues a sound notification. In its application, SACPS makes it possible

to deal with a number of situations denoted in the inference model as follows:

Rule-1: if (camera_capture = object) and (object = has_distance) then system_output = give notified the user based on an object for navigation.
Rule-2: if (camera_capture = object) and (object = has_low_brightness) then system_output = increase brightness.
Rule-3: if Rule-2 is True then do Rule-1

Table 5 reveals the algorithm in pseudo-code form for the SACPS mechanism on the smart glass's architecture based on the five existing rules, namely Rule-1 to Rule-3.
Objects (O) would be identified based on context knowledge $C_i \in \{C1, C2, C3\}$, the results of which became a reference for the inference of the formulated model. The process of determining identification was carried out during monitoring (M) with the output in the form of $Cv_i \in \{C_{V1}, C_{V2}, C_{V3}, C_{V4}\}$. The output would be sent to the analyzer_manager section which was at the cognition level (CG).

Table 5:
Sacps adaptive algorithm for smart glasses

Adaptation of CPS Pattern

```
Input
O ← C1, C2, C3
Do
Let
O ← inference model
// Monitoring (M)
For O in runtime artifact, do
   O ← get value C1, C2 and C3 in runtime artifact
   For each values C1, C2 and C3 in SACPS artifact, do
      If Cvi in runtime artifact, then
         Send information Cvi to analyzer_manager
      endif
   endfor
endfor

// Cognition (CG)
For each Cvi in analyzer_manager, do
   If Cv1, Cv2, Cv4 is True, then
      If Cv1 is True, then
         Increase brightness from O
      Endif
      O ← predict_object and predict_distance
      new_decision ← O
   else
      O ← the object cannot be detected
      new_decision ← empty
   endif
endfor

// Configuration (CF)
If CG contain new_decision, then
   System ← release a sound notification
   For each system in runtime artifact, do
      Send information to M
   endfor
endif
```

Next, Cv_i in analyzer_manager was processed in the Cognition (CG) section to obtain a new decision from the results obtained in M. This process was executed by analyzing Cv_i which would produce a new decision O. The output from CG was in the form of a decision command for the configuration (CF) section. If new_decision contains a new decision, the system will issue a notification sound as the final result of the process of object detection.
The model development process was conducted based on an extension of the machine learning/deep learning method of John et al. [28] adapted to the requirements of this investigation. Hence, the development stages had been determined as represented in Figure 5.

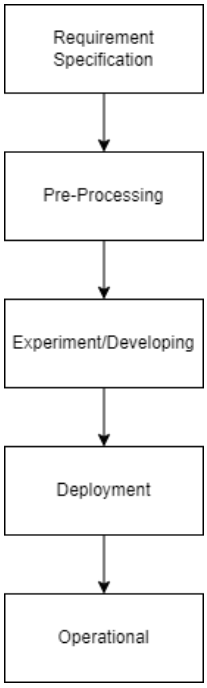


Figure 5: Development stages

The experimental process requires an investigative environment to meet every experimental need while being performed. Therefore, it is necessary to prepare appropriate specifications to fulfill experimental needs. Hence, the obtained results are maximal. The required specifications for the training process are adjusted to the requirements of the Dist-YOLOv3 algorithm Vagjl et al. [10] referring to the specifications of the employed device. The required specification consists of (a) Python 3.9.6; (b) Tensorflow 2.6.0; and (c) CUDA. The training process was conducted using a batch size of 2 and a learning rate of 0.001. The Adam optimizer was used, and training was performed for a maximum of 40 epochs with early stopping based on validation mAP. The loss function combined cross-entropy loss for object classification and smooth L1 loss for distance estimation. The Xception backbone was initialized with pretrained ImageNet weights to leverage transfer learning. Additionally, a single-head self-attention block with an embedding

dimension of 256 was integrated into the detection head. Query, key, and value matrices were generated via 1×1 convo lutions, followed by layer normalization and ReLU activation for feature refinement.

The utilized data for the model creation process originated from a dataset created by KITTI (Karlsruhe Institute of Technology and Toyota Technological Institute) Geiger et al. [25]. The dataset was called KITTI 3D Object Detection Evaluation 2017. It refers to a data set covering 3D objects. Also, it consisted of 7481 training data and 7518 test data. The data pre-processing process was executed by following the steps proposed by Vajgl et al. [10] as manifested in Figure 6. The data were separated into two parts, namely training data and test data obtained from the training data section of the KITTI Dataset. This occurred due to only the data in the training section containing distance values. As a result, the actual distance was required to be compared with the predicted distance from the detection results for testing purposes. The emphasis of preprocessing was on label processing containing prominent information for the training process. Information (e.g. bounding box points, class index, and distance value) were elements that should be included in label annotations.

In the experimental stage, the training process was carried out by making adjustments to the employed architecture. The Darknet53 architecture was substituted by the Xception architecture [11] with the addition of an attention mechanism layer proven to improve the performance of the applied architecture in YOLO [26], [27], [28]. In proving that the created model is better than the model of Vajgl et al. [10], we compared the pre-trained model from this study with the pre-trained model available at https://gitlab.com/EnginCZ/yolo-with-distance established by Vajgl et al. [10]. This comparison aims to compare state-of-the-art methods discussed in the related work section, particularly the work of Vajgl et al. [10]. Figure 7 illustrates the difference in train loss and validation loss values.

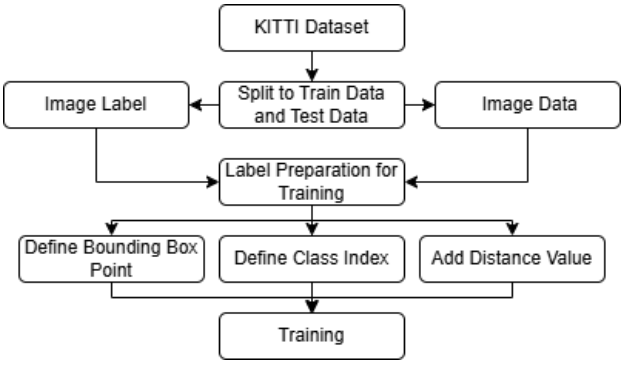


Figure 6: Pre-processing data

The employment of an additional layer in the form of an attention mechanism has been proven to reduce the loss value to a greater extent than without adding this layer. Figure 7 designates the difference in loss values with the results of train loss and validation loss reaching 16,031 and 17,565. These results are quite different from the pre-trained model results of Vajgl et al. [10]. The next comparison is related to the Pascal VOC AP (Average Precision) evaluation measurement for each class. These measurements are usually applied to evaluate the performance of object detection models [33]. This is an attempt to enhance the proposed SACPS detecting model.

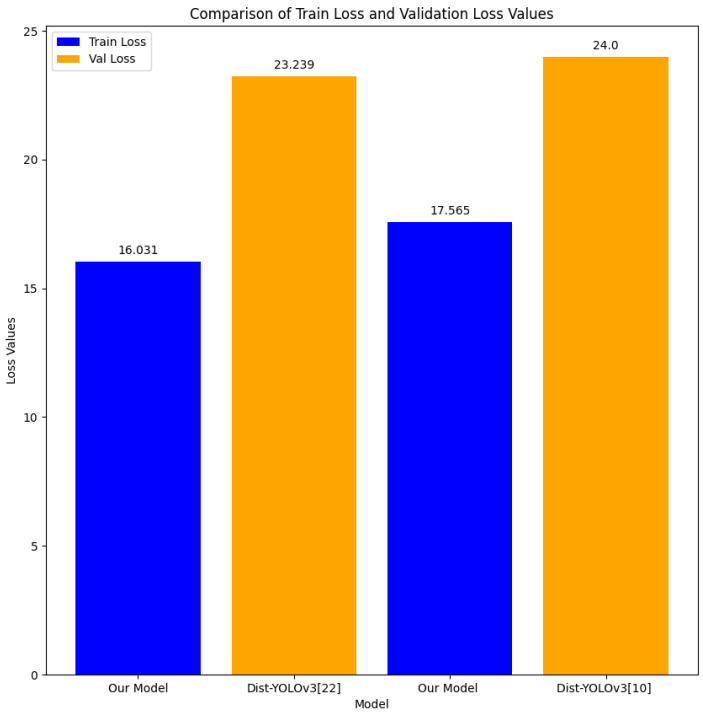


Figure 7: Comparison of train loss and validation loss

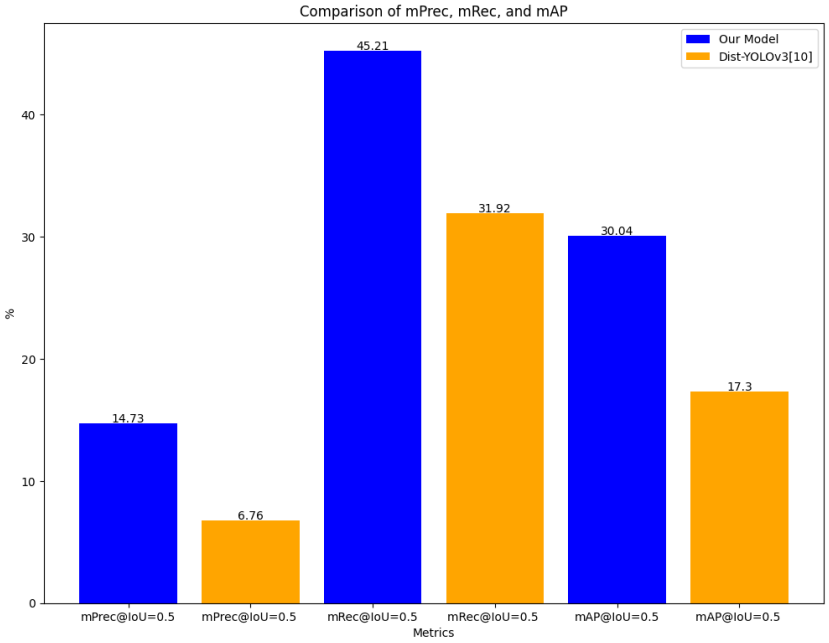


Figure 8: Comparison of mPrec, mRec, and mAP values

Figure 8 indicates a comparative detecting performance based on Pascal VOC AP measurements with a threshold or Intersection over Union (IoU) of 0.5. The model developed in this study was superior in evaluation results with mPrec, mRec, and mAP values of 14.73%, 45.21%, and 30.04% respectively observed. This proves that the pre-trained model can detect objects that exist properly. Hence, it enables to increase in the mAP value greater than the original model [10] available on public links. However, due to the limitations of existing devices, we can only use a batch number of 2 so the training process is time-consuming.

To further evaluate the optimization behavior of the proposed model, we conducted a convergence analysis based on the training and validation loss values recorded over 40 epochs. This analysis aims to assess whether the training process led to stable convergence and to identify any signs of overfitting or instability that might affect the model's generalization capability.

As depicted in the loss convergence curves in Figure 9, the training loss decreased steadily and stabilized at approximately 16.03, indicating proper convergence. Although the validation loss initially started at a high value due to uncalibrated predictions, it consistently declined over 40 epochs, eventually reaching a value of 23.24. This trend confirms the model's effective learning of generalizable features without significant overfitting. The relatively high absolute loss values are attributed to the multi-objective nature of the loss function and unnormalized scaling.

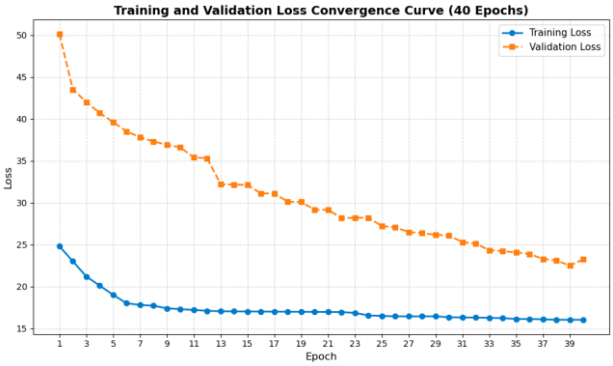


Figure 9: Training and validation loss convergence curve

After reaching a better pre-trained model compared to the pre-trained model [10], we then carried out experiments on context knowledge and adaptive requirements on $C_1, C_3 \in \{C_{V3}, C_{V1}\}$. The experiment was conducted by detecting images with low light intensity. The utilized light intensity level was based on the average RGB value. Hence, we gained an equation to calculate the increased new light intensity in equation (5).

$$I_{new} = I_{old} \times F \tag{5}$$

Where I_{new} was the new intensity updated based on I_{old} multiplied by F, where F was the factor enhancing the light intensity with F > 1, equation (5) was employed if the $I_{old} < 50$. Also, it manifested which value was taken from the average light intensity value in the images. Furthermore, the F value would be adjusted to the old intensity value detected with $F \in \{F > 1\}$. Briefly, we conducted experiments with images indicating an average light intensity below 50. Technically, Table 6 describes the changing results of the intensity of the utilized images.

The experiment in Table 6 discloses good adaptive results because the improvement in the intensity value was adjusted to the previous light intensity value. This was aimed at avoiding the damage of the obtained information results in the detected images. In addition, excessively increasing the intensity could damage the existing color composition and could create noise in the image. The scenario of $C_1, C_3 \in \{C_{V3}, C_{V1}\}$ was effectively performed to increase the light intensity in the image on average by 100.0703.

Figure 10 shows increased light intensity conducted by the system based on miscellaneous schemes from C_3 containing various values of old brightness (I_{old}). The resulting new brightness (I_{new}) would not be increased excessively even though the I_{old} value was close to the value of 50 as represented by Table 6 in the 25th sample. The I_new value produced a fairly stable value if $I_{old} \in \{I_{old} > 25\}$. However, the I_{new} value underwent unstable changes when the $I_{old} \in \{I_{old} < 10\}$ value. The stability of the I_newvalue has a very prominent role in the final results of object and distance predictions. This was proven in the 4th sample experiment for $I_{old} < 10$ and the 17th sample for $I_{old} > 25$.

Table 6:
Results of adaptation of C_{V3} light settings

No. Sample	Light Intensity before (I_{old})	Light Intensity after (I_{new})
1	3.3443	67.4892
2	5.5522	83.6164
3	7.7493	77.9420
4	8.7250	87.4341
5	9.9340	99.1287
6	11.1267	67.5903
7	14.2915	86.0231
8	16.4727	98.8303
9	18.6484	110.8143
10	19.8362	113.6794
11	22.0120	88.2736
12	25.3866	101.8137
13	27.5531	109.3286
14	28.5278	111.4813
15	29.7263	113.5586
16	31.8851	95.8494
17	36.2576	108.2096
18	37.4274	110.3538
19	38.4252	112.0422
20	39.6189	113.5254
21	41.8004	100.2741
22	45.1630	107.8529
23	47.3357	110.9795
24	48.3229	112.2473
25	49.5122	113.4192
Average light intensity after (I_{new})		100.0703

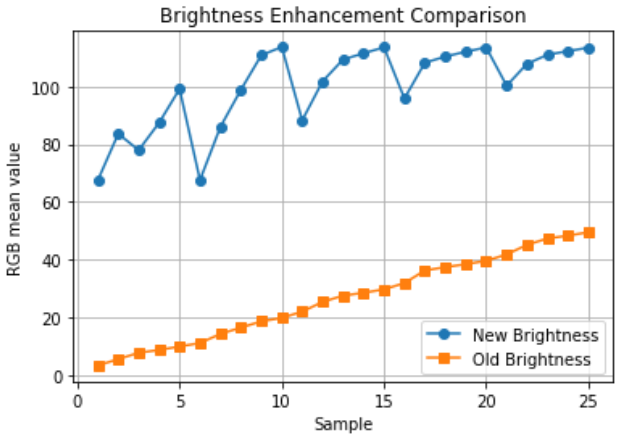


Figure 10: Brightness enhancement comparison



(a)

(b)

Figure 11: (a) 4th sample with a light intensity value of 8.7250. (b) 17th sample with a light intensity value of 36.2576.

Figure 11 illustrates the input images of the 4th and 17th samples, both of which have undergone light intensity enhancement. These two examples represent different segments of the I_{old} range: the 4th sample with $I_{old} < 10$, and the 17th sample with $I_{old} \approx 45$. As depicted in Figure 13, the subsequent outputs—object prediction and distance estimation—exhibited markedly different behaviors under the same enhancement procedure. In the case of the 4th sample, the original image was extremely dark, making essential visual features such as edges and textures virtually indiscernible. Upon applying light intensity scaling, the image became noticeably brighter, but at the cost of amplifying noise and artifacts. This led to unstable or erroneous object detection, with the model often missing or misclassifying key targets.

Furthermore, distance prediction in this sample was unreliable due to the distortion introduced by aggressive enhancement from such a low baseline. By contrast, the 17th sample, with moderately low lighting, retained a sufficient amount of visual information. The light adjustment process yielded a stable and visually coherent image (I_{new}), resulting in more accurate object detection and consistent distance estimation. This comparison demonstrates that while the proposed model exhibits

improved robustness under typical low-light conditions, its performance significantly deteriorates when the initial image intensity falls below a critical threshold (approximately I_{old} < 10). Although the implemented brightness enhancement method—using a scaling factor FFF when I_{old} < 50—effectively improves visibility in low-light scenarios, it remains a rule-based and non-learning approach. This mechanism was chosen to demonstrate a lightweight, self-triggered adaptation behavior within the SACPS context. However, the instability observed in extremely dark cases highlights the limitations of fixed-rule strategies. Future improvements will involve integrating adaptive, learning-based enhancement modules (e.g., LLNet, Zero-DCE, or transformer-based models) that provide more context-aware correction while mitigating noise and preserving structural detail, thereby enhancing both object recognition and distance estimation reliability in diverse lighting conditions.

To demonstrate that the proposed model outperforms its predecessors, we conducted an ablation study on four model configurations: Dist-YOLOv3 [10], Dist-YOLOv3+Xception, Dist-YOLOv3+Attention, and Dist-YOLOv3+Xception+Attention (Proposed Method). Furthermore, to support the model's generalisation capability, we evaluated its performance under varying lighting conditions by simulating reduced illumination on the KITTI test data. The results of this ablation study are presented in Table 7.

Table 7:
Ablation study

Model Variant	Light Intensity	mAP (%)	mPrec (%)	mRec (%)
Dist-YOLOv3 [10]	100%	17.30	6.76	31.92
	80%	15.48	5.97	29.04
	60%	13.12	4.88	26.04
	40%	10.93	3.75	22.01
Dist-YOLOv3 + Xception	100%	23.61	11.25	37.88
	80%	21.30	9.94	34.41
	60%	18.42	8.11	30.75
	40%	15.67	6.42	26.08
Dist-YOLOv3 + Attention	100%	22.63	10.63	35.82
	80%	19.80	8.90	31.99
	60%	17.01	7.34	27.45
	40%	14.83	6.09	25.17
Dist-YOLOv3 + Xception + Attention	100%	30.04	14.73	45.21
	80%	27.46	13.06	41.00
	60%	24.85	11.30	36.48
	40%	21.78	9.64	31.59

The results indicate that both Xception and the attention mechanism independently improve performance over the baseline under all lighting conditions. The Xception architecture in Dist-YOLOv3 proves especially beneficial in low-light scenarios. The complete model, which combines both Xception and attention, achieves the best overall results, demonstrating the effectiveness and robustness of the proposed approach in adaptive object recognition tasks.

To fulfill the context knowledge and adaptive requirements in $C_1, C_2, C_3 \vee C_1, C_2 \in \{C_{V1}, C_{V2}, C_{V3}, C_{V4}\}$, the system should be able to produce a sound output of notification in the form of identified objects in front of it. These requirements were built through the Google Text to Speech (gTTS) library covering a sample rate of 22050-44100 Hz. As a result, it provides clear sound with clear quality of each pronounced word. A notification will come out of the system if there is an object that is 5 meters away in front of you. Figure 12 demonstrates the sound waves resulting from the detection of objects located 5 meters in front of the machine.

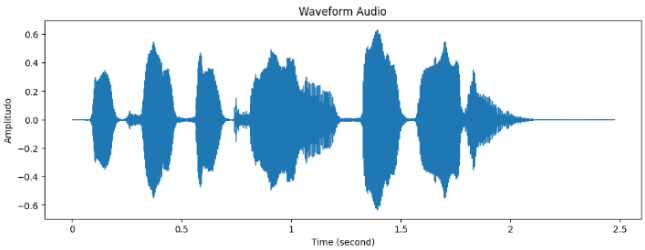


Figure 12: Audio waveforms from system output

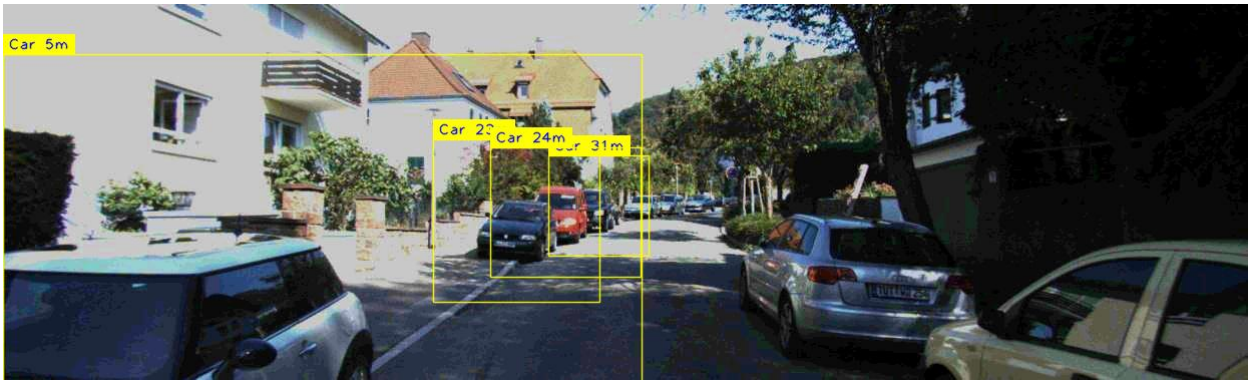
The audio waves in Figure 12 illustrate that there is a car object 5 meters in front of the camera. This indicates one of the successful final results of detecting and fulfilling the needs of $C_1, C_2, C_3 \vee C_1, C_2 \in \{C_{V1}, C_{V2}, C_{V3}, C_{V4}\}$ by all the experimental scenarios cultivated in this study.

Internal validity refers to the extent to which research results can be attributed to the manipulation of independent variables rather than other factors. The threat to internal validity in this study refers to the irrelevant use of data in various environments. In this case, these data refer to the adopted data for the object recognition model training process. For this reason, it may cause significant accuracy gaps and reduce the adaptability of the system in diverse environments.

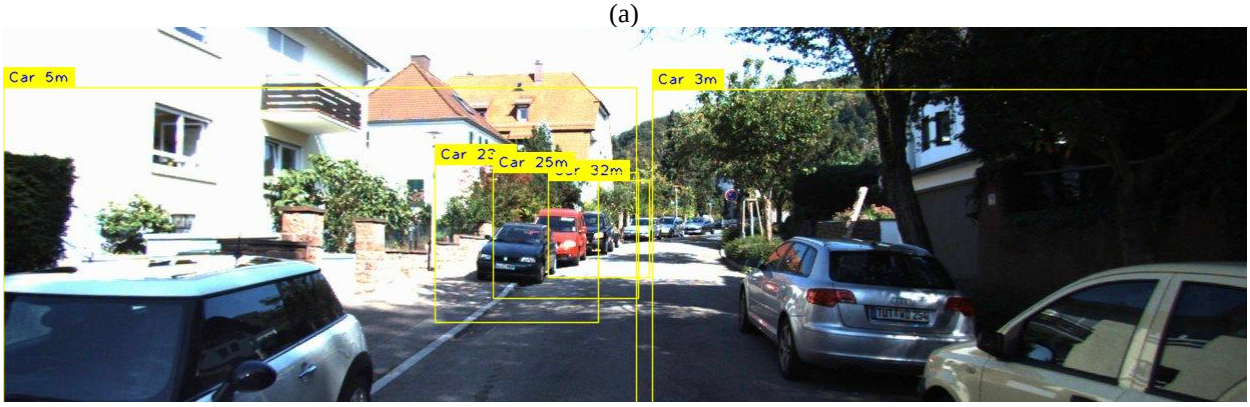
Construct validity refers to the extent to which a test or measuring instrument measures a particular concept or construct. Threats to construct validity encompass inadequate definitions and supportive effects. The threat of inadequate definitions is caused by very limited object classes and the adaptation of the existing classes in the KITTI dataset. As a result, the model is unable to recognize objects comprehensively. Besides, this will also cause the inaccurate object recognition model's metric measurements. One threat to the supportive effect is that if other factors (e.g. voice assistance or user interaction with additional devices) assist in object recognition, the results may not fully reflect the capabilities of the object recognition model itself.

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(a)



(b)

Figure 13: (a) Results of increased light intensity, object prediction, and distance prediction in the 4th sample. (b) Results of increasing light intensity, object prediction, and distance prediction on the 17th sample

The evaluative results, in terms of object recognition and adaptation, yielded excellent results when measured by the corresponding metrics. Conversely, this has not ruled out the possibility of threats to the conclusive validity. Although it can be inferred that the object recognition model produced by this research exhibits better performance than previous models, several cases highlight the model's shortcomings. One of them is when objects are closely situated to each other or partially captured by the camera. This makes the model unable to accurately recognize what object is being detected. Furthermore, if adaptive ability is considered successful, there is a possibility of adaptive failures when the light intensity is increased. When the adaptation process for increasing light intensity occurs, the results occasionally indicate an effect on the image, such as loss of quality in miscellaneous aspects.

The limited number of employed object classes and the existing dataset environment have opened new threats to external validity. Even though the entire evaluation results of this research are auspicious, it needs to be re-emphasized that testing miscellaneous environmental characteristics depends on the data used, so it is highly recommended to make improvements by adding to the data used, either by adding data from independent collection results or by combining it with the available dataset.

5 Discussions

Our model introduces two main architectural enhancements to the original Dist-YOLOv3: replacing the Darknet53 backbone with the Xception architecture and integrating an attention mechanism layer before the head. These improvements have shown a notable increase in detection performance. In terms of quantitative evaluation, our model achieves a mean Average Precision (mAP) of 30.04%, compared to the baseline mAP of approximately 17.3% reported by Vajgl et al. [10], marking a 12.74% improvement. Additionally, the mean recall increased to 45.21%, and the mean precision reached 14.73%. We compared the pre-trained model from this study with the pre-trained model available at https://gitlab.com/EnginCZ/yolo-with-distance. These metrics demonstrate a better detection capability in real-world scenarios, especially in complex environments with occlusions or variable lighting conditions. The improvement is primarily due to:

- Xception Backbone: With its depthwise separable convolutions, Xception enables deeper and more efficient feature extraction than the original Darknet53. This enables the model to capture fine-grained spatial features more accurately.

- Attention Layer: The attention mechanism selectively emphasizes relevant spatial features and suppresses irrelevant or noisy ones, improving both classification and localization accuracy.

However, the performance gain comes at a cost. The model incurs higher computational complexity, especially during training, and exhibits higher loss values (16.031 training loss and 17.565 validation loss). This is attributed to:

- The use of a small batch size (2) due to limited hardware resources, which affects training stability and convergence speed. The inclusion of a distance loss term, which adds to the total loss function and increases its numerical magnitude.

- The use of historical label-based distance data from KITTI may not perfectly align with real-time physical constraints.

In addition to detection accuracy, our model also incorporates a self-adaptive light intensity enhancement mechanism to address challenges in low-light environments. This component is crucial for ensuring visual clarity and maintaining object recognition performance in varying illumination conditions. The experimental results indicate that the brightness enhancement system successfully increases image intensity in dark environments, with an average post-adaptation brightness of 100.07, up from initial values of less than 50. This enhancement is designed to avoid overexposure by applying a proportional intensity factor based on the original image brightness. Two representative cases were highlighted:

- In the 4th sample (initial brightness: 8.72), although the enhancement increased visibility, it also introduced noticeable noise and partial information loss, which negatively affected detection accuracy.

- In the 17th sample (initial brightness: 36.26), the enhancement achieved more stable brightness with minimal noise, leading to more accurate object and distance predictions.

These findings reveal a critical insight: while adaptive brightness enhancement is beneficial, it must be applied carefully depending on the original light level. Excessive enhancement in extremely dark images may degrade the image quality and impair the detection process. This aspect reflects a trade-off between adaptation robustness and prediction accuracy. In future iterations, incorporating learned enhancement filters or adaptive gain control mechanisms may help optimize this process and reduce noise in low-light scenarios.

Despite the observed improvements, several limitations remain in the current implementation. First, tuning hyperparameters—particularly those related to attention mechanisms and light adaptation thresholds—required a series of empirical iterations due to the absence of prior benchmarks in this domain. This process introduces complexity and may compromise reproducibility if thorough documentation is not provided. Second, although the attention layer improves detection accuracy, it inevitably increases computational load during inference, which could impact responsiveness—especially on low-power wearable platforms. While inference time was not formally measured in this study, the additional layers are expected to introduce some delay due to their sequential nature and computational requirements. Lastly, deployment in varied environments presents practical challenges: indoor scenes often suffer from occlusion and low-light noise, while outdoor settings may include background clutter and high dynamic range lighting. These differences complicate generalization and suggest the need for environment-aware calibration in future iterations.

6 Conclusion and further studies

This paper introduces a CPS-based object recognition model with automatic adaptive capabilities to address uncertain real-world objects in a CPS environment characterized by adaptive strategies. The main focus of the experiment is on the adaptive strategies of the CPS-based object recognition system and the performing specifications of the system. The research results report that this system can make object recognition better, notably for blind people during navigating practices. This experiment was carried out in the context of application development in the field of self-adaptive cyber-physical systems (SACPS), particularly in smart glasses. The utilization of adaptive strategies (e.g. increasing light intensity and object recognition based on context) has been fruitful. Increased light intensity is carefully processed to maintain image quality and avoid noise.

Moreover, this study has successfully developed a machine learning/deep learning-based object recognition model superior to previous models. This model can amplify the mAP value and accuracy value in recognizing objects. Even though there are limitations to the applied devices, this improvement signifies a highly significant result. In particular, the experimental results also denote that the system can issue a sound notification to its users when there is an object within five meters in front of them. Given this fact, it meets the adaptive requirements in a CPS environment. Overall, this study has fruitfully developed an adaptive CPS-based object recognition model that can advance the quality of object recognition, notably for blind people in the context of smart glasses. The results of this scrutiny showcase remarkable

potentials in cultivating the life quality of the blind people while performing daily activities.

Based on the entire experimental results, some major findings attracted our attention. As an example, at the detecting evaluative model stage, the comparison of train loss and validation loss revealed better results than the detecting model of Vajgl et al. [10] with average reduction values of 26.7% and 26.8% respectively. Besides, the Pascal VOC AP metric indicated that the values of each metric component had increased for both the mPrec, mRec, and mAP elements with an average increase of 7.97%, 13.29%, and 12.74%, respectively. Moreover, the adaptability of our model was represented in the form of adaptation to changes in light intensity. The evaluative results indicated that, after the adaptation process, the average light intensity of the enhanced images reached 100.0703 (I_{new}). This reflects the ability of the proposed adaptive mechanism to consistently raise low-light image brightness to an optimal level. Such enhancement significantly contributed to the improved functionality and adaptability of the object detection model, particularly in varying illumination conditions.

Our proposed adaptive strategy has an indispensable role in the real-world object recognition process based on broader cues in multiple quality attributes. Among them, precision, recall, and average accuracy are determined based on the ability to adapt to the surrounding environment. This indicates that efforts to resolve the problems of recognizing real-world objects have been restricted to certain cues without adaptability.

This paper opens up new opportunities for future investigation. To illustrate, the adaptive strategy of a CPS-based object recognition system can be directly employed based on an effective adaptive environment. In this experiment, we applied the model to the needs of a smart glasses system. However, it does not rule out the possibility of being applied to other system needs in the real world. Our model has the potential to be applied to several applications, including autonomous driving, robot vision, smart doors, and so on.

Shortly, we plan to conduct further experiments to optimize this adaptive strategy of object recognition to invigorate its accuracy and performance through a lighter model when being implemented. As an illustration, improving adaptability through the addition of adaptive features (e.g. system failure management, self-scheduled recognition model updates, and identification of new object classes) to increase system knowledge. In addition, replacing the YOLO-based model with the latest version is one way to optimize the object recognition model. Applying automatic parameter selection methods in the training process is the primary step in enhancing such an object recognition model. Further, we will also upgrade the designed smart glasses device to be able to provide thorough and specific features for other needs of blind people. As part of this plan, we aim to conduct a pilot usability study involving individuals who are blind or visually impaired, in collaboration with assistive technology communities. This will allow us to evaluate the system's real-world applicability, user satisfaction, and interaction flow, which are essential for ensuring its practicality and accessibility. In addition, we will validate the system in more realistic environments for visually impaired users by employing data from indoor navigation or close-range object interaction, which are more representative of real-world scenarios faced during daily activities.

The impacts and importance of our proposed model are related to the sustainability of object recognition systems for long-term needs. Considering that the variety of real-world cues recognized by a recognition system has the potential to undergo rapid and unpredictable changes. Our model offers adaptability to adjust the state of the system based on specific contexts, notably increased accuracy in recognizing objects affected by light intensity. Also, this represents an achievement of the objectives of this work, namely developing a generic model for adapting CPS services when recognizing real-world objects as heterogeneous and strongly influenced by their environmental conditions.

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Hybrid Optimization of CO_2 Emissions and Energyin High-Performance Concrete Using KNN, Elastic Net, and Artificial Rabbits Optimization Models

Xiong Gao[1], Yan Li[2]*, Yansheng Wu[3]
[1]Faculty of Environmental and Chemical Engineering, Kunming Metallurgy College, Kunming City, Yunnan Province, 650033, China
[2]Faculty of Architecture Engineering, Kunming Metallurgy College, Kunming City, Yunnan Province, 650033, China
[3]Logistics and Infrastructure Management Center, Kunming Metallurgy College, Kunming City, Yunnan Province, 650033, China
E-mail: feng_4587@163.com
*Corresponding author

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In this study, an integrated machine learning framework is proposed to accurately predict and minimize CO_2 emissions and energy consumption in the manufacturing of High-Performance Concrete (HPC). The methodology combines K-Nearest Neighbor (KNN) and Elastic Net Regression (ENR) models with the Artificial Rabbits Optimization (ARO) algorithm for hyperparameter tuning, and employs Recursive Feature Elimination (RFE) to isolate the most influential input variables. A dataset comprising key HPC mix components was curated from experimental sources and subjected to rigorous preprocessing. Among the tested models, the hybrid ENR + ARO (ENAR) model achieved the best performance for energy prediction with an R^2 of 0.986 and RMSE of 52.63 MJ/m³, while the KNN + ARO (KNAR) model yielded the highest accuracy for CO_2 emission prediction with an R^2 of 0.992 and RMSE of 7.57 kg/m³. The application of RFE improved model performance by 12.4% in RMSE reduction for energy prediction and 9.6% for CO_2 estimation, by eliminating redundant features. Cement and superplasticizer content were identified as the most influential predictors. These results provide a reliable and interpretable framework for enhancing the sustainability of concrete production through data-driven mix optimization.

Povzetek: Študija združi KNN, Elastic Net in metahevristiko Artificial Rabbits Optimization z RFE za napovedovanje ter zmanjšanje CO_2 emisij in energije v visokozmogljivem betonu. Najboljša modela (ENAR za energijo, KNAR za CO_2) izpostavita cement in superplastifikator kot ključna dejavnika.

1 Introduction

HPC constitutes a specialized category of concrete characterized by superior performance relative to conventional concrete, as evidenced by selected properties such as durability, service life, and low maintenance requirements [1]. HPC is made up of Portland cement, water, coarse aggregates, and various chemical and mineral admixtures [2]. However, HPC manufacturing utilizes significant amounts of energy and adds a lot to CO_2 emissions, especially from the manufacture of cement, which is responsible for around 8% of CO_2 emissions worldwide [3]. Recently, the environmental impact of HPC has become a focal point, especially when large-scale construction projects increase demand for this material [4], [5]. Heavy machinery employed in performing tasks such as structural simulations, material testing, and optimization is widely used throughout the design and process stages of these projects [6]. Such machines need, by necessity, high-powered systems that consume considerable amounts of energy and produce considerable CO_2 emissions both during their operation and through the lifecycle of manufacture and use [7], [8].

Among other major concerns in the sustainability of construction projects is energy consumption, which is important both ecologically and economically [9]. In general, large computer systems used in high-performance applications for BIM, 3D modeling, and complex simulations consume a huge amount of energy [10]. DVFS and power capping can be two ways of managing power that, once optimized, could reduce energy usage without necessarily affecting computational performance. These methods allow energy resources to be used more efficiently while sustaining the high processing power required for modern construction tasks [11]. The construction industry has to be strengthened with green computing and Energy Efficiency (EE) for it to be sustainable. Only then would modern construction projects result in a minimum environmental impact coupled with economic viability [12].

1.1 Related works

Properties and mixture design of Ultra-High-Performance Concrete (UHPC) have a direct influence on the forecast of CO_2 emissions and energy consumption for manufacturing HPC. Normally, binder content between 800-1000 kg/m³ has the highest impact on the carbon footprint of UHPC. In UHPC, cement hydration is not fully achieved, with only 30–40% of the cement reacting because of a reduced water-to-binder ratio. The remaining unreacted cement acts mainly as an inert filler [13]. The employment of SCMs comprising FA and GGBS results not only in a reduction in cement consumption but also in lowered carbon emissions [14], [15]. That is important because, by replacing the conventional cement with SCMs, during the manufacturing process of UHPC, CO_2 emissions are greatly reduced, thus having a direct influence on the carbon footprint in general. Apart from this, binder content optimization plays a vital role in determining desired mechanical properties; hence, energy consumption is of concern. Such a dense microstructure and high compressive strength through SCM incorporation and superplasticizers increase energy requirements, mainly during the curing phase. For the curing of composites, additional methods like heat or autoclave curing imply greater energy use [16], [17]. On the other hand, the addition of SCMs like 20% FA or 3.2% $nano - CaCCO_3$ has been reported not only to improve mechanical properties but also to have a potential influence on the EE of the manufacturing process by possibly reducing the curing energy required for optimum performance [18], [19].

1.2 Objective

This paper, therefore, aims to develop a new framework for the estimation of feature importance and the optimization of model performance with the multi-objective approach of KNN, ENR, and ARO. This paper designs a new feature importance estimation framework and optimizes model performance for a multi-objective approach that makes use of a combination of KNN, ENR, and ARO techniques. The framework, therefore, performs FS and enhances predictive accuracy by making good use of the complementary strengths of the combined models on a wide range of datasets for the assurance of robustness and completeness when performing ML optimizations. First, RFE is applied as an iterative feature selector that keeps only a subset of the most informative features. RFE eliminates the least important features according to their ranking regarding model performance and iteratively updates the feature importance. This recursive procedure retains only the most relevant features, hence reducing the dimensionality, avoiding overfitting, and improving the efficiency of the model. From the optimization perspective, the ARO novel metaheuristic algorithm inspired by nature has been introduced to optimize hyperparameters of model performance. Indeed, this new ARO metaheuristic mimics rabbit foraging behavior in its process of performing an effective search for near-optimal solutions towards high-dimensional, possibly complicated spaces. Since it optimizes models with numerous interactions among so many variables in the interaction, ARO is certainly the right addition to improve optimization model selection methodologies. The KNNs together with ENR and ARO algorithms systematically model refinement and ensure some combinations of opted features and parameters by a model optimized towards superior predictive result outcomes. In this respect, this study presents a hybrid modeling approach, combining the strengths of KNN, ENR, and ARO, thus building increased model interpretability, performance, and robustness.

2 Methodology

2.1 K-Nearest Neighbor (KNN)

The simplicity, effectiveness, and application of the KNN algorithm are well known. It is related to both RF and ANN in that it can be used in both regression and classification applications. For everyday use, it was fitting since its general concepts were obvious and simple. Both regression and classification problems can train non-linear decision boundaries. This makes it further flexible when these limits are set, and thereby allows the value of K to change. Compared to other algorithms, K-NN does not have to have a separate training phase. In simple words, it uses one hyperparameter, K, which also makes modifying the rest rather easy. The main concept behind KNN involves locating a set of K samples in the calibration data that are similar to the unknown samples, typically using a distance metric. For this purpose, matching groups of samples must be determined. KNN compares the result with a group of K samples and computes the mean value of the response variables to find the classes of the unknown samples [20]. Hence, the effectiveness of the KNN algorithm depends heavily on the choice of K [21]. The three distance functions used in regression projects for calculating the distances between the neighborhood data points are given by Eqs. (1-3).

$$F(e) = \sqrt{\sum_{i=0}^{f}(x_i - y_i)^2} \tag{1}$$

$$F(ma) = \sum_{i=0}^{f}|x_i - y_i| \tag{2}$$

$$F(mi) = \left(\sum_{i=0}^{f}(|x_i - y_i|)^q\right)^{\frac{1}{q}} \tag{3}$$

The Manhattan distance function is denoted by $F(ma)$, the Minkowski distance function by $F(mi)$, and the Euclidean distance function by $F(e)$. The order parameter q is used to calculate the distances between the data points x and y, which are represented by the words x_i and y_i, respectively, for their ith dimensions. The flowchart for the KNN model is demonstrated in Fig. 1.

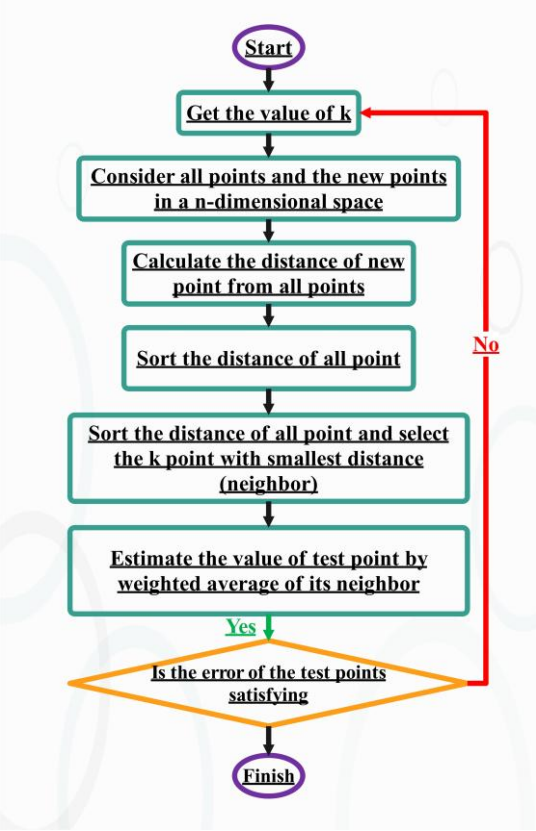


Figure 1: The flowchart of the KNN model

2.2 Elastic Net Regression (ENR)

ENR is a high-performance linear regression technique that combines the best features of L1 (Lasso) and L2 (Ridge) regularization techniques. Its dual regularization technique enhances the model's interpretability and prognostic performance, reduces multicollinearity and overfitting in high-dimensional datasets, and encourages sparsity and stability in coefficient estimates [22], [23].

- **Direct Communication**

$P(y|\beta,\sigma^2) = N(y|X\beta,\sigma^2 I_n)$ this is the probability of the article, where β is a p-vector that contains the regression coefficients. Where predictor variables are included in the $n \times p$ dimensional matrix X. Given that the vector y and the columns of X are considered to be demeaned, the model is specified without an intercept. In this approach, the linear regression parameters are typically estimated as follows:

$$\hat{\beta} = \underset{\beta}{arg\,min}\,(y - X\beta)^T(y - X\beta) + \lambda J(\beta) \quad (4)$$

Considering a nonnegative punishment function J and a regularization value $\lambda > 0$.

$$p(\beta|\lambda,\alpha) \propto exp[-\lambda\,\{\alpha|\beta|^2 + (1-\alpha)|\beta|_1\}] \quad (5)$$

This study offers a completely normalized and explicated version of the prior, extending the Bayesian connection to the ELR approach.

$$p(\beta|\alpha,\lambda,\sigma^2) \propto exp\left[-\frac{\lambda}{2\sigma^2}\,\{\alpha|\beta|^2 + (1-\alpha)|\beta|_1\}\right] \quad (6)$$

For given values of σ^2 and α, the posterior mode corresponds to the naïve elastic net estimate with an overall penalty of λ, and this is expressed by the formulation that states the penalty λ's magnitude is now $2\sigma^2$. This prior is a double-exponential distribution when $\alpha = 0$. When $\alpha \approx 1$, it exhibits the characteristics of a normal distribution. As demonstrated by the integration of Eq. (6), the normalization constant can be expressed in closed form until the evaluation of the univariate standard normal Cumulative Distribution Function (CDF). The appropriate density function on a smaller scale than the previous one.

$$p(\beta|\lambda,\alpha,\sigma^2) = \prod_{j=1}^{p}\left\{(0.5).N^-\left(\beta_j|\frac{1-\alpha}{2\alpha},\frac{\sigma^2}{\lambda\alpha}\right) + (0.5).N^+\left(\beta_j| -\frac{1-\alpha}{2\alpha},\frac{\sigma^2}{\lambda\alpha}\right)\right\}, \quad (7)$$

In truncated normal distributions, N^- and N^+ signifies density functions that have been suitably modified.

$$N^+(t|m,s^2) \equiv \frac{N(t|m,s^2)}{\phi(m/s)}\,1(t \geq 0)\ And\ N^-(t|m,s^2) \equiv \frac{N(t|m,s^2)}{\phi(-m/s)}1(t < 0), \quad (8)$$

The tails of a normal distribution always contain the univariate standard normal CDF and $\phi.\beta_j$ since the location parameter for the positive component in Eq. (7) is always negative. The following is an alternative perspective on the previous: Let $Z = \{-1,1\}^p$ be the set of all p-vectors that can have members ± 1 and let $\mathcal{O}_z \subset \mathbb{R}^p$ be the orthant that corresponds to each vector z in Z. $\beta j \geq 0$for $\mathcal{Z}_j = 1$ and $\beta j < 0$for $\mathcal{Z}_j = -1$ if $Z.\beta j \geq 0$. Consequently, the preceding Eq. (10) may be expressed as follows:

$$p(\beta|\lambda,\alpha,\sigma^2) = 2^{-p}\phi\left(\frac{\alpha-1}{2\sigma\sqrt{\alpha/\lambda}}\right)^{-p} \times \sum_{z\in\mathcal{Z}} N\left(\beta|\frac{\alpha-1}{2\alpha}z,\frac{\sigma^2}{\lambda\alpha}I_p\right)1(\beta \in Oz). \quad (10)$$

To show that the prior is piecewise normal, an "orthant normal" prior is constructed by describing each piece over a separate orthant. The following results are obtained when the prior is represented regarding λ_1 and λ_2.

$$p(\beta|\lambda_1,\lambda_2,\sigma^2) = 2^{-p}\phi\left(\frac{-\lambda_1}{2\sigma\sqrt{\lambda_2}}\right)^{-p} \quad (11)$$

$$\times \sum_{z\in\mathcal{Z}} N\left(\beta|-\frac{\lambda_1}{2\lambda_2}z,\frac{\sigma^2}{\lambda_2}I_p\right)1(\beta\ \in\ Oz).$$

From now on, the (λ_1,λ_2) formulation is used unless otherwise noted. The posterior distribution is obtained by multiplying the probability of the regression model by Eq. (11) and using the Bayes theorem.

$$p(\beta|y,\lambda_1,\lambda_2,\sigma^2)=\sum_{z\in\mathcal{Z}}\omega_z N^{[z]}(\beta|\mu_z,\sigma^2R), \tag{12}$$

A weighted sum of the normal distributions represents a multivariate normal orthant integral following the trimming of the 2^P Orthant.

$$N^{[z]}(\beta|m,s)\ \equiv\ \frac{N(\beta|m,s)}{P(z,m,s)}1(\beta\ \in\ Oz),$$
$$where\qquad P(z,m,s)\ =\int_{\mathcal{O}_z}N(t|m,s)dt, \tag{13}$$

Since every component is defined on a different orthogon, the prior and posterior are both multivariate piecewise normal. Its posterior distribution is its collection of parameters.

$$R\ =\ \left(X^TX+\lambda_2\,I_p\right)^{-1}$$
$$and \tag{14}$$
$$\mu_z=\hat{\beta}_R-\frac{,\lambda_1}{2}Rz,$$

The ridge regression estimate in this instance is $\hat{\beta}_R = RX^Ty$, with a penalty of λ_2. The weights for each orthostat are the last components of the posterior.

$$\omega_z=\omega^{-1}\frac{P(z.\mu_z,\sigma^2R)}{N(0|\mu_z,\sigma^2R)},$$
$$where\ \ \omega=\sum_{z\in Z}\frac{P(z,.\mu_z,\sigma^2R)}{N(0|\mu_z,\sigma^2R)}. \tag{15}$$

2.3 Artificial Rabbits Optimization (ARO)

While the hares' natural persistence strategies inspired the endurance algorithm, the ARO algorithm was motivated by them. The model for this method was the bypass exploration tactic used by hares to emerge from their burrows in search of food. So that they are not startled when they are approached, hares dig tunnels near their hiding places. In cases where food is necessary or sufficient for them, they gravitate toward it by nature. A habit known as circumvention foraging occurs when rabbits, when their energy levels are high enough often look for food outside of their burrows. But, in times of low energy, they frequently merely plunge into nearby burrows to find cover [24].

- **Vitality Decrease (Switch between Exploitation and Exploration)**

Depending on their energy level, hares may decide to purposefully conceal or postpone foraging. An energy factor $A(t)$, which mimics the hare's decision-making process, is computed using Eq. (16). The hare chooses not to graze if $A(t)\ >\ 1$. Otherwise, if $A(t)$ equals or is less than 1, random concealment is used.

$$\mathrm{A(t)}=4\left(1-\frac{\mathrm{t}}{\mathrm{T}}\right)\ln\frac{1}{\mathrm{r}} \tag{16}$$

In this case, r is a number between 0 and 1 that is chosen at random.

- **Circumvent Foraging (Exploration)**

According to Eq (16), hares hunt for food at random and distant from their burrows based on the positions of their friends to defend themselves against potential predators: There are several variables in the formula. $\overrightarrow{x_i}(t)$ represents the ith hare's location at time t, whereas $\overrightarrow{S_i}(t+1)$. Represents the candidate's position at time $t\ +$ 1. T is the maximum number of cycles, and L is the hare's speed of movement. The variable n stands for the hare population size, and d signifies the count of variables requiring optimization in the problem. Furthermore, r_1, r_2 and r_3 represent the three random values in the interval (0,1) and n_1 has a standard normal distribution. R is the operating function that mimics the features of a hare running, while c is the mapping vector.

- **Unpredictable Concealment (Exploitation)**

Using Eq. (17), each rabbit burrow produces a collection of d lairs. To find refuge and evade any predators, the rabbit randomly selects various hiding places:

$$\overrightarrow{\mathrm{b_{i,j}}}(\mathrm{t})\ =\overrightarrow{\mathrm{x_i}}(\mathrm{t})+\mathrm{H}\times\mathrm{g}\times\overrightarrow{\mathrm{x_i}}(\mathrm{t}),\mathrm{i}$$
$$=1,\dots,\mathrm{n\ and\ j}=1,\dots,\mathrm{d} \tag{17}$$

$$\mathrm{H}=\frac{\mathrm{T}-\mathrm{t}+1}{\mathrm{T}}\times\mathrm{r_4} \tag{18}$$

$$\mathrm{g(k)}=\begin{cases}1\ \text{if k}=\mathrm{j}\\ 0\ \text{else}\end{cases}\quad \mathrm{k}=1,\dots,\mathrm{d} \tag{19}$$

$$\overrightarrow{\mathrm{S_i}}(\mathrm{t}+1)=\ \overrightarrow{\mathrm{x_j}}(\mathrm{t})+\mathrm{U}$$
$$\times\left(\mathrm{r_4}\times\overrightarrow{\mathrm{b_{i,r}}}(\mathrm{t})-\overrightarrow{\mathrm{x_i}}(\mathrm{t})\right)\mathrm{i}=1,\dots,\mathrm{n} \tag{20}$$

$$\mathrm{gr(k)}=\begin{cases}1\ \text{if k}=|\mathrm{r_5}\times\mathrm{d}|\\ 0\ \text{else}\end{cases}\quad \mathrm{k}=1,\dots,\mathrm{d} \tag{21}$$

$$\overrightarrow{\mathrm{b_{i,r}}}(\mathrm{t})=\overrightarrow{\mathrm{x_i}}(\mathrm{t})+\mathrm{H}\times\mathrm{gr}\times\overrightarrow{\mathrm{x_i}}(\mathrm{t}),$$
$$\mathrm{i}=1,\dots,\mathrm{n} \tag{22}$$

$$\overrightarrow{\mathrm{x_i}}(\mathrm{t}+1)=\begin{cases}\overrightarrow{\mathrm{x_i}}(\mathrm{t})\mathrm{f}\left(\overrightarrow{\mathrm{x_i}}(\mathrm{t})\right)\le\mathrm{f}\left(\overrightarrow{\mathrm{s_i}}(\mathrm{t}+1)\right)\\ \overrightarrow{\mathrm{s_i}}(\mathrm{t}+1)\mathrm{f}\left(\overrightarrow{\mathrm{x_i}}(\mathrm{t})\right)>\mathrm{f}\left(\overrightarrow{\mathrm{s_i}}(\mathrm{t}+1)\right)\end{cases} \tag{23}$$
$$\mathrm{k}=1,\dots,\mathrm{d}$$

According to Eq. (22), where H is the hiding factor, jth lair for the ith rabbit and r_4 and r_5 are arbitrary values in the interval (0,1), the arbitrarily selected lair that the ith rabbit would take refuge in is $\overrightarrow{b_{i,r}}(t)$.

2.4 Performance evaluators

To evaluate the predictive performance of the proposed models for CO_2 emissions and energy consumption in HPC manufacturing, the following metrics were employed:

- **Root Mean Square Error (RMSE):** Quantifies the square root of the average of squared differences between predicted and observed

values. RMSE penalizes large errors more than small ones, which is crucial in industrial applications where severe misestimation could lead to significant overuse of materials or excess emissions.

- **Mean Absolute Error (MAE):** Measures the average magnitude of errors in predictions without considering their direction. MAE is easy to interpret in physical units (e.g., MJ/m³ or kg/m³), which makes it particularly valuable for production engineers.
- **Mean Absolute Percentage Error (MAPE):** Indicates the average relative error as a percentage. MAPE is helpful for understanding how large the prediction error is compared to actual values, which supports decision-making for mix design optimization.
- **Nash–Sutcliffe Efficiency (NSE):** Compares the predictive power of a model to the mean of observed values. Values close to 1 indicate excellent predictive accuracy. An NSE > 0.9 is generally considered highly acceptable for environmental and materials modeling.
- **Coefficient of Determination (R^2):** Represents the proportion of variance explained by the model. An R^2 > 0.95 was set as a practical benchmark for high accuracy in this study, based on prior literature in concrete property prediction.

$$R^2 = \left(\frac{\sum_{i=1}^{n}(b_i - \bar{b})(d_i - \bar{d})}{\sqrt{\left[\sum_{i=1}^{n}(b_i - \bar{d})^2\right]\left[\sum_{i=1}^{n}(d_i - d)^2\right]}} \right)^2 \quad (24)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(d_i - b_i)^2} \quad (25)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(P_i - T_i)^2 \quad (26)$$

$$WAPE = \max\left[\frac{|b_i - m_i|}{b_i}\right] \quad (27)$$

$$NSE = 1 - \frac{\sum_{i=1}^{N}(m_i - b_i)^2}{\sum_{i=1}^{N}(b_i - \bar{b})^2} \quad (28)$$

In the context of predicting CO_2 emissions and energy consumption in HPC manufacturing, b_i in this study stands for the expected values for each measurement and p_i for the observed readings for each sample. The actual measured values for each sample are represented by T_i, whereas the word $\bar{b}$ indicates the mean of the anticipated values across all samples. Furthermore, ($\bar{T}$) denotes the mean of all measured values in the sample set, whereas $\bar{m}$ represents the average of the observed values. These symbols are crucial for computing and assessing the precision of the models created to forecast CO_2 emissions and energy usage during the manufacturing of HPC.

2.5 Rationale for model selection

KNN and ENR were selected for their complementary strengths. KNN is a non-parametric algorithm that captures non-linear relationships, while ENR is a linear model that can handle multicollinearity through regularization. The use of both allows the assessment of whether linear or non-linear models are more suitable for the given problem. ARO was integrated to enhance the exploration of hyperparameter space, especially for fine-tuning the models beyond traditional grid or random search methods.

Additionally, Recursive Feature Elimination (RFE) was incorporated to eliminate irrelevant or redundant features, reducing dimensionality and computational overhead while improving generalization.

3 Data description

The data from Kaggle makes a deep simulation of a concrete mixture with varying features that influence the environmental consequences (www.kaggle.com/datasets/taruneshburman/energy-consumption-prediction). This creates more opportunities for exploration in studies seeking to forecast concrete compressive strength with the influence of sustainability as an important factor. Feature descriptions are attached below:

Cement [kg/m^3]: Amount of cement utilized in the mixture. This accounts for so much in concrete strength but leads to high embodied CO_2 emissions due to the very energy-intensive production process.

Water [kg/m^3]: The water used to hydrate it. While an optimum water-to-cement ratio yields a durable concrete mixture, excess water reduces strength and, therefore, impairs sustainability.

Superplasticizer (kg/m^3): It is a chemical additive to the concrete mixture, enhancing workability without adding water. It improves performance but does not contribute much to environmental sustainability.

Coarse Aggregate [kg/m^3]: Is grit or any other similar material in the mixture; this variable influences the concrete strength and ecological impact due to its consumption of raw materials.

Fine Aggregate (kg/m^3): The weight of sand or other similar materials that would affect the structural integrity and sustainability of the mix.

Age (days): Time taken for curing concrete in days. Early-age strength is an essential factor in the construction schedule of concrete, as strength increases with age.

Compressive Strength (MPa): The target variable is the axial load-carrying capacity of the concrete. Measured in MPa, it is predicted based on input features.

Embodied CO_2 (kg): Lists the amount of CO_2 a mixture produced through its making and material usage, showing the carbon footprint.

Energy Consumption: Energy consumption means the total sum of all energy required to produce concrete mixture ingredients in megajoules. It is about features of EE related to the mix.

Resource Consumption (kg): This gives the sum of the mass of all the ingredients consumed in kg for one cubic meter of concrete production kind of resource intensity indicator for the mix.

Table 1 shows the descriptive statistics for all variables included in the dataset: maximum and minimum values, means, and the value of the standard deviation. The correlation between the input and output data is shown in Fig. 2 along with the matching correlation plot. Embodied CO_2 and cement, for instance, shows a substantial connection in the figure, suggesting a considerable link between the two variables.

Table 1: The statistical properties of dataset variables

Category	Variables	Indicators			
		Max	Min	Avg	St. Dev.
Input	Cement	499.9	201.4	347.1	87.6
Input	Water	220.0	150.2	185.5	20.5
Input	Superplasticizer	29.9	0	15.1	8.7
Input	Coarse Aggregate	1099.9	800.2	947.1	85.9
Input	Fine Aggregate	899.3	600	748.2	86
Input	Age	364	1	178.7	105.5
Input	Compressive Strength	615.2	87.8	226.9	109.1
Input	Resource Consumption	2652.76	1857.35	2242.98	150.27
Output	Energy Consumption	2849.19	1009.03	1919.69	436.161
Output	Embodied CO_2	507.878	198.304	350.711	82.7324

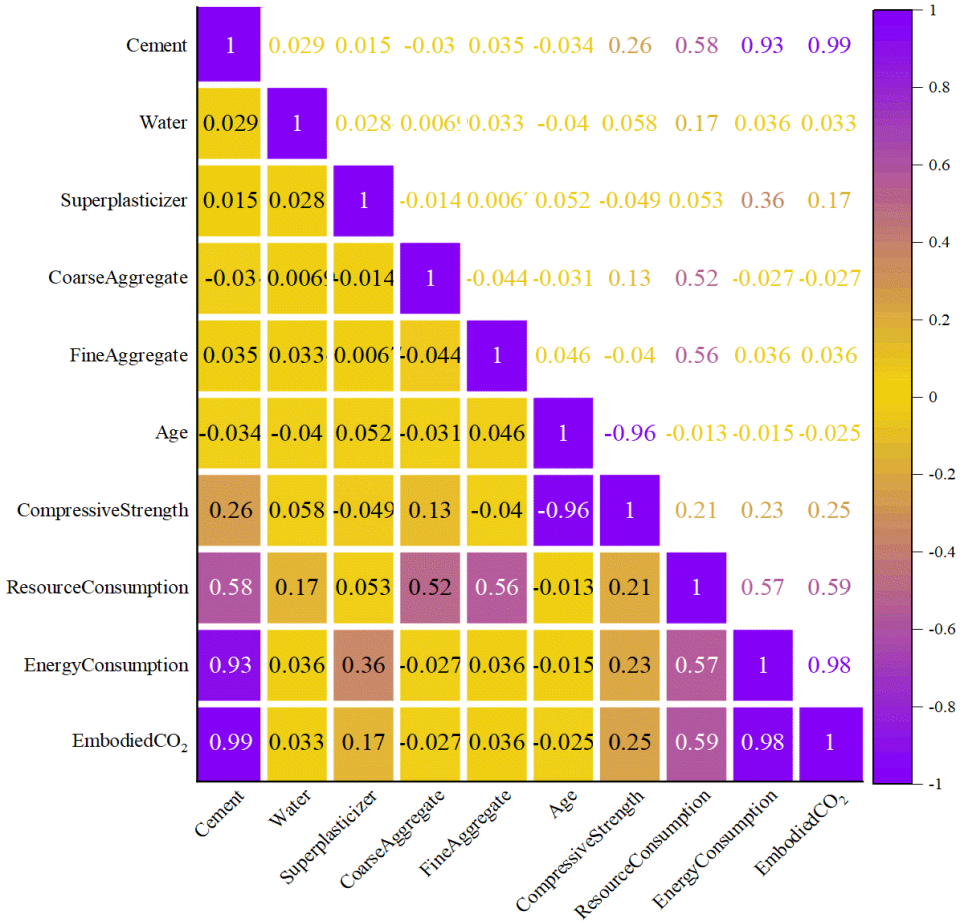
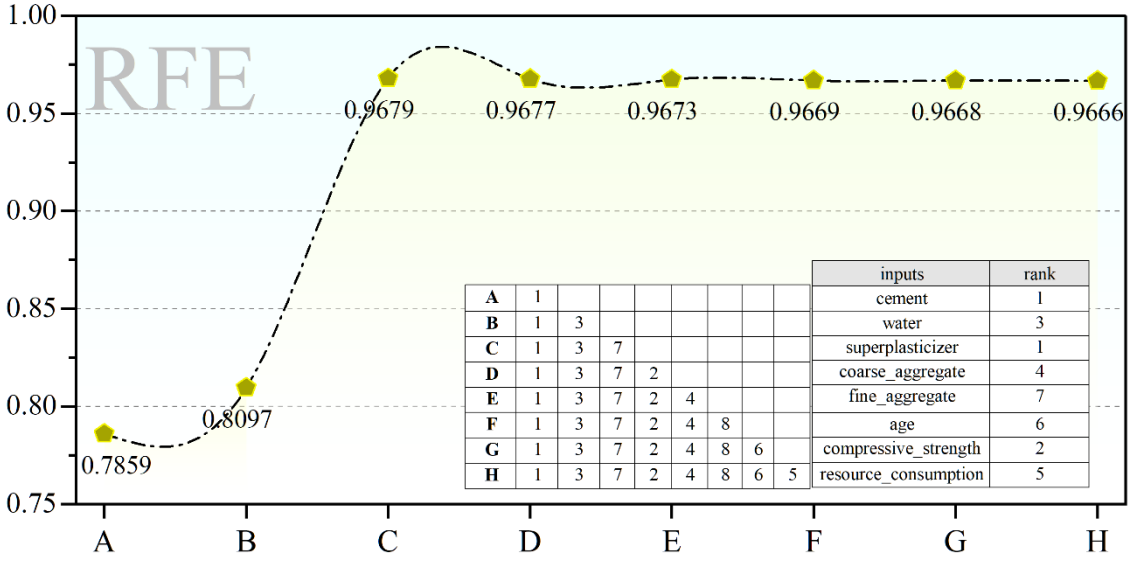


Figure 2: The correlation plot for input and output

3.1 Feature selection analysis for CO_2 emissions and energy consumption in HPC manufacturing: RFE process and key influences

The given analysis in Fig. 3 discusses the FS results for emissions and energy consumption in HPC manufacturing. This plot illustrates the RFE process, ranking features by their importance to model performance. The ranking score is displayed on the vertical axis, while the quantity of considered features is shown on the horizontal axis. The highest score, approximately 0.9679, reflects strong model performance with a specific feature subset. Beyond a certain point, additional features contribute minimally, suggesting that the most relevant information is captured within the top-ranked features. The ranking is topped by cement with rank 1, which signifies that cement has the highest impact on both CO_2 emissions, and energy consumption. Superplasticizer also holds the top rank, showing how critical it is in performance enhancement and resource use. Compressive Strength follows with a rank of 2, indicating it has a high influence. Water ranks third, which gives it considerable importance but less than cement and superplasticizers. Medium influences are given to Coarse Aggregate ranked 4 and Resource Consumption ranked 5, while low influences are accorded to Age and Fine Aggregate ranked 6 and 7, respectively, in this context. The quality of the cement, superplasticizer, and mainly, how green it can be is going to be the priority to reduce the amount of CO_2 emitted. This can be further refined by the optimization of water, compressive strength, and aggregate for performance versus greening balance. Other additional factors concerning resource consumption could also be considered; interaction between several features might also be modeled for better understanding in future work.



A	1							
B	1	3						
C	1	3	7					
D	1	3	7	2				
E	1	3	7	2	4			
F	1	3	7	2	4	8		
G	1	3	7	2	4	8	6	
H	1	3	7	2	4	8	6	5

inputs	rank
cement	1
water	3
superplasticizer	1
coarse_aggregate	4
fine_aggregate	7
age	6
compressive_strength	2
resource_consumption	5

Figure 3: Feature Importance for CO_2 Emissions and Energy Consumption Using RFE

The raw data underwent several preprocessing steps to ensure quality and compatibility with ML models:

- **Missing Values:** Samples with missing target values were discarded. Missing feature values (<5%) were imputed using mean imputation.
- **Normalization:** All features were normalized using min-max scaling to the range [0, 1] to avoid dominance of features with larger magnitudes.
- **Outlier Detection:** Z-score analysis was used to identify extreme outliers, which were reviewed manually and retained only if physically plausible.
- **Data Splitting:** The dataset was split into 70% training and 30% testing sets using stratified random sampling to preserve target distribution balance.

4 Results and discussion

The outcomes of utilizing ML regression models to forecast CO_2 emissions and energy usage in HPC manufacturing are shown in this section. Model performance indicators like RMSE, R^2, MSE, WAPE, and NSE are displayed in the figures and tables. These metrics demonstrate how well the models anticipate the intended results.

- **Analysis**

Fig. 4 compares the performance of two optimization models, namely ENAR and KNAR, in predicting embodied CO_2 emissions, and energy consumption in HPC manufacturing. The RMSE value across 200 iterations is used to assess the convergence trends. The result of the embodied CO_2 emissions for the ENAR model depicts a gradual convergence in terms of reducing the RMSE value to an ending value of 12.588 after roughly 150 iterations. It gives a good, moderate accuracy for the prediction. For the KNAR model, a final lower value of the RMSE was obtained at 7.952, which shows fast and consistent convergence; hence, this proves that the KNAR model is more efficient and more precise in modeling the CO_2 emissions. On the other hand, for energy consumption, ENAR demonstrates a very similar

convergence pattern for an RMSE value flattened to 69.706. It performs medium in developing its accuracy across subsequent iterations. Within this set of models, in turn, comes the performance realized by KNAR, yielding ultimately a better endpoint RMSE result of 83.815. Slower convergence against higher error is indicative of the resulting lower reliability in terms of the point accuracy of the forecasts pertinent to energy consumption. On the whole, KNAR performed better in predicting embodied CO_2 emissions than ENAR, while ENAR outperformed in energy consumption predictions owing to its lower RMSE values. These results further indicate that although KNAR is more robust for modeling CO_2 emissions, ENAR may be more suitable for the optimization of energy consumption in the manufacture of HPC.

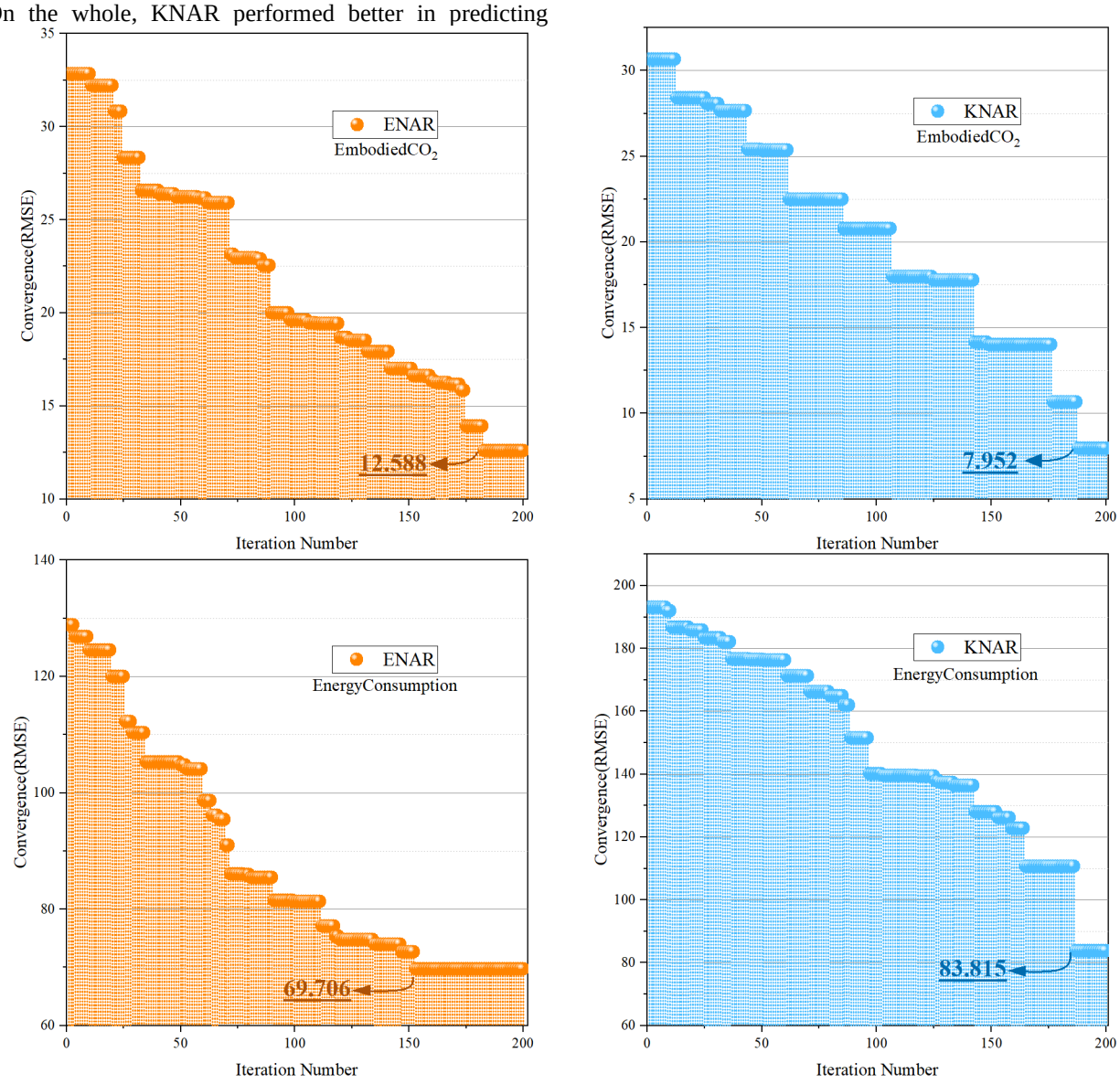


Figure 4: Scatter plot for the convergence Curve of the hybrid models

Energy consumption and embodied CO_2 analysis by Tables 2 and 3 underlines technical performance for the hybrid models of KNN, KNAR, EN, and ENAR through different metrics: the RMSE, R^2, MSE, WAPE, and NSE.

For energy consumption (Table 2): KNN achieves an R^2 value of 0.948 during all phases and an RMSE of 103,498. KNAR shows a notable improvement with an R^2 of 0.968 and an RMSE of 82.629. EN further improves upon this with an R^2 of 0.973 and an RMSE of 71,490. ENAR outperforms all models with the greatest R^2 of 0.986 and the lowest RMSE of 52.626, indicating superior performance in energy consumption prediction.

For embodied CO_2 (Table 3): KNN performs reasonably well with an R^2 of 0.977 and an RMSE of 12.588. KNAR excels in an R^2 of 0.992 and an RMSE of 7.573, showing significant improvement. EN achieves an $R^2$of 0.961 and an RMSE of 16.348, while ENAR follows with an R^2 of 0.975 and an RMSE of 13.083. KNAR outperforms all models in predicting embodied CO_2. In Conclusion, ENAR consistently delivers the best performance for energy consumption prediction, while KNAR is the most accurate model for predicting embodied CO_2, providing the best balance of R^2 and error (RMSE) in both cases.

Table 2: The results of hybrid models for the EN and KNN (Energy Consumption)

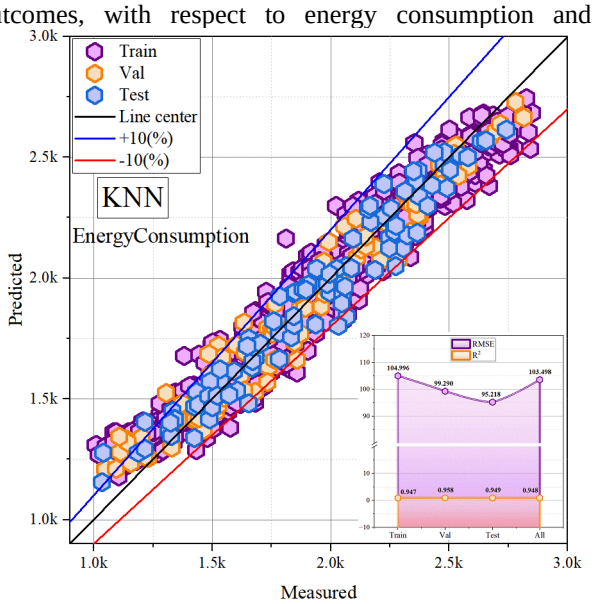
Model	Phase	Index values			
		Train	Validation	Test	All
KNN	RMSE	104.996	99.290	95.218	103.498
	R^2	0.947	0.958	0.949	0.948
	MSE	11024.228	9858.529	9066.412	10711.876
	WAPE	0.044	0.042	0.041	0.044
	NSE	0.942	0.952	0.946	0.944
KNAR	RMSE	83.815	79.345	76.026	82.629
	R^2	0.967	0.974	0.968	0.968
	MSE	7025.029	6295.656	5779.911	6827.580
	WAPE	0.035	0.034	0.033	0.035
	NSE	0.963	0.969	0.966	0.964
EN	RMSE	75.491	56.511	48.207	71.490
	R^2	0.970	0.986	0.987	0.973
	MSE	5698.893	3193.454	2323.951	5110.855
	WAPE	0.030	0.024	0.020	0.028
	NSE	0.970	0.984	0.986	0.973
ENAR	RMSE	55.364	40.752	38.896	52.626
	R^2	0.984	0.993	0.991	0.986
	MSE	3065.210	1660.707	1512.922	2769.531
	WAPE	0.022	0.018	0.017	0.021
	NSE	0.984	0.992	0.991	0.985

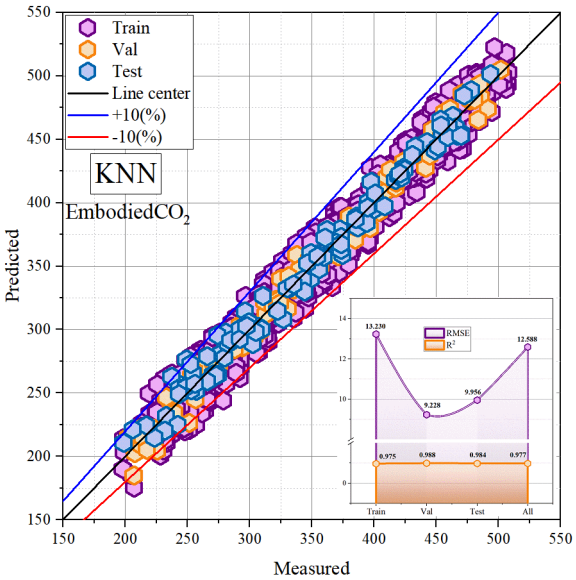
Table 3: The outcomes of hybrid models for the EN and KNN (Embodied CO2)

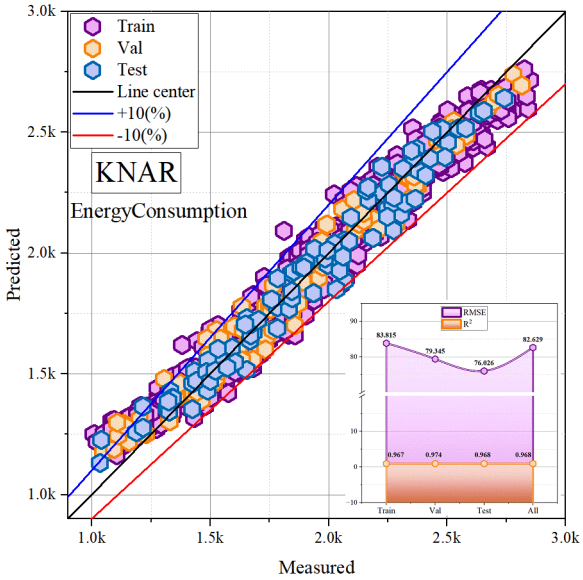
Model	Phase	Index values			
		Train	Validation	Test	All
KNN	RMSE	13.230	9.228	9.956	12.588
	R^2	0.975	0.988	0.984	0.977
	MSE	175.028	85.158	99.119	158.450
	WAPE	0.030	0.021	0.023	0.029
	NSE	0.975	0.988	0.984	0.977
KNAR	RMSE	7.952	5.607	6.012	7.573
	R^2	0.991	0.996	0.994	0.992
	MSE	63.237	31.439	36.148	57.348
	WAPE	0.018	0.013	0.014	0.017
	NSE	0.991	0.996	0.994	0.992
EN	RMSE	15.951	18.338	17.342	16.348
	R^2	0.963	0.953	0.952	0.961
	MSE	254.433	336.276	300.753	267.249
	WAPE	0.038	0.046	0.044	0.040
	NSE	0.963	0.952	0.950	0.961
ENAR	RMSE	12.589	15.124	14.665	13.083
	R^2	0.977	0.968	0.965	0.975
	MSE	158.471	228.733	215.051	171.155
	WAPE	0.030	0.038	0.037	0.032
	NSE	0.977	0.968	0.965	0.975

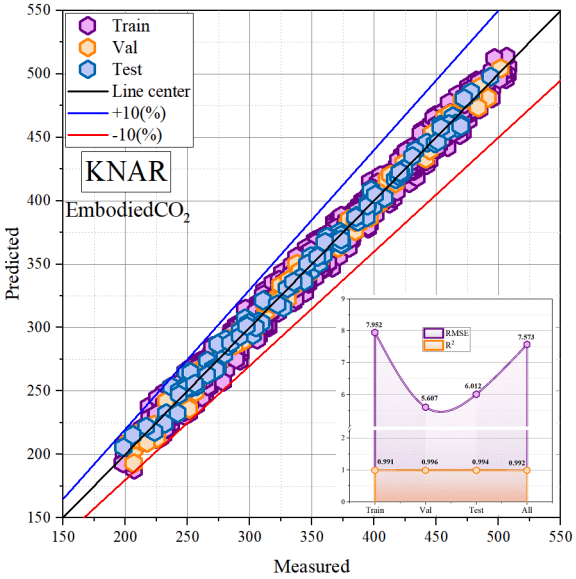
Fig. 5 provides comparisons in train versus test and validation data related to energy use and embodied CO_2, having as the line at the center the perfect prediction, while two dotted lines reflect ± 10% margin, showing the boundaries for the prediction errors. For energy consumption, KNN performed well in moderate clustering around the central line, though it generally featured substantial scatter, especially in the validation and test datasets, with higher prediction errors for extreme values. Even though similar results were obtained with KNN for the embodied CO_2 due to its lower RMSE, the wider scatter limits its accuracy for a proper prediction of consumption. The results show that KNAR offers improved clustering, with reduced scatter and smaller error margins, reflecting a higher robustness across datasets. Furthermore, it consistently remains nearer to the centerline, resulting in enhanced predictive capabilities for both energy usage and embedded CO_2. EN produces

tighter clustering than KNN, especially for lower and moderate energy consumption values, while it lacks the robustness of KNAR. The ENAR produces the best clustering with the least scatter and the highest accuracy in prediction on all datasets. Stability and precision in the outcomes, with respect to energy consumption and embodied CO_2, are superior in the current model when compared with other models. Overall, KNAR and ENAR show the highest reliability and accuracy, hence the best to use in assessing environmental impacts in HPC manufacturing.









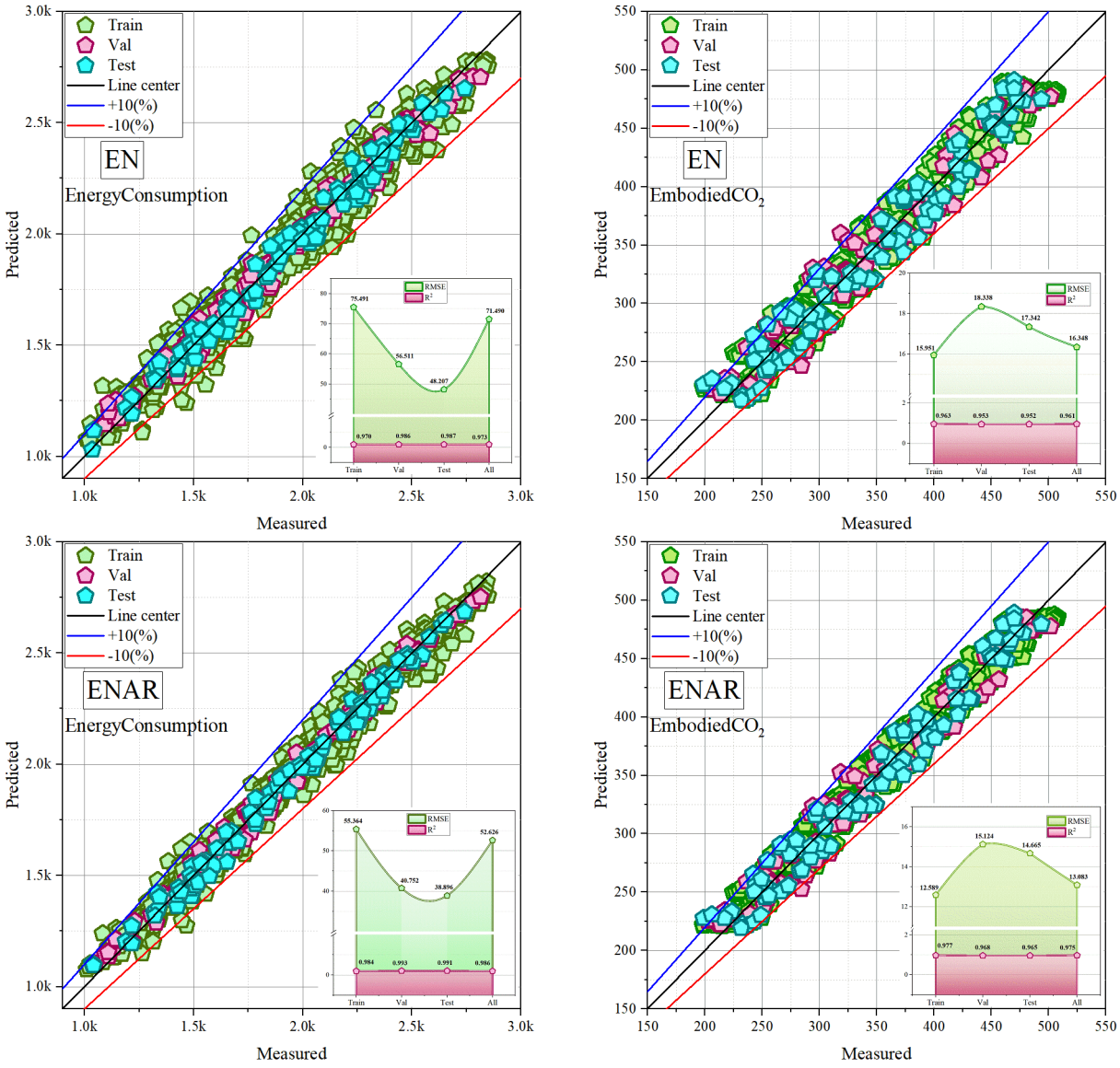


Figure 5: The scatter and line symbol plot for developed hybrid models

Fig. 6 is a violation plot that compares the four ML model errors according to KNN, KNAR, EN, and ENAR across Train Validation and Test in a way that densities may be visualized at different error values.

For Embodied CO_2: KNN is highly variable, with larger error margins, especially when it comes to validation and test datasets, a feature that ascribes to the low reliability of this method. The results indicate that the error distributions for all datasets are tighter, and better stability is displayed, especially at the validation and testing phases by KNAR. EN decreases error variance further than KNN, achieving higher accuracy and stability. Yet, it has a slightly weaker robustness performance than KNAR. ENAR achieves the tightest error distributions with the highest accuracy and robustness on all the datasets.

For Energy Consumption: KNN has a high variability in error, especially in validation and testing datasets, which means it has a poor generalization capability. KNAR has reduced variability, particularly tighter error clustering in the test dataset, which represents an increased reliability in predictive capabilities. EN has tighter error distributions than KNN, especially for smaller values, but is slightly worse than KNAR. ENAR performs the best with the lowest error margins and is consistent on all datasets. Conclusion: ENAR is the most accurate in energy consumption prediction, while KNAR is the best in embodied CO_2 prediction.

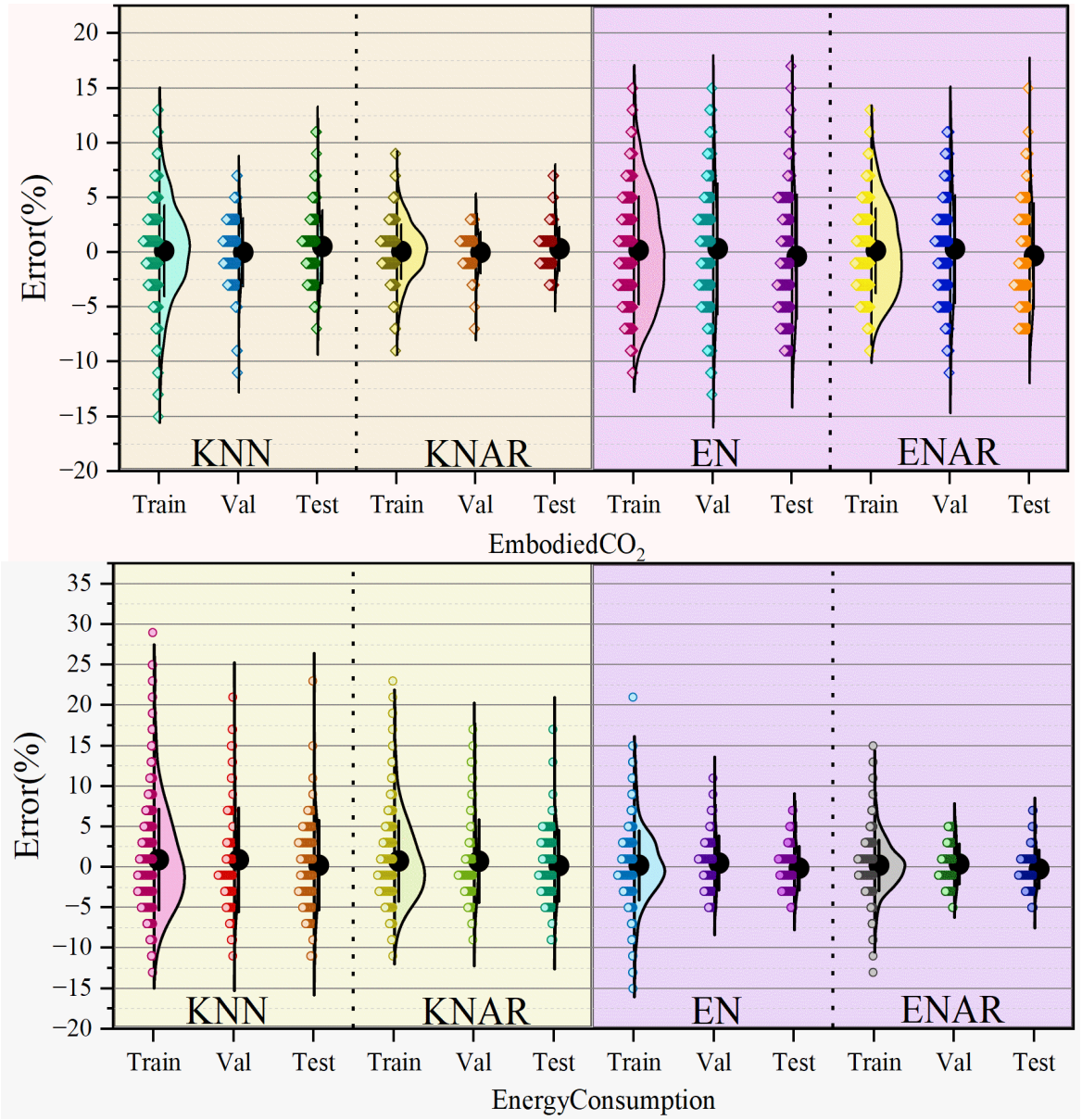


Figure 6: Comparing the errors of the developed models

The Taylor diagram in Fig. 7 provides a way to evaluate model performance against a reference dataset, combining the correlation coefficient, r, and standard deviation, σ, in one diagram. It can be applied to evaluate the accuracy of prediction in HPC manufacturing. In HPC manufacturing, this figure works very well for evaluating forecast accuracy. KNAR performs best in terms of embodied CO_2 since it is closest to the diagram's reference point, indicating a strong correlation and low RMSE. On the other hand, ENAR performs better than ENAR, whereas K-NN and KNAR, which are less accurate, perform worse. Additionally, ENAR outperforms all competing models in energy consumption predictions, obtaining the greatest correlation and lowest RMSE. While EN scores lowest, showing the largest RMSE and the shortest R^2 value, KNN and KNAR perform moderately. While KNAR performs better in estimating embodied CO_2, ENAR is shown to be the most accurate model overall for energy consumption forecasts.

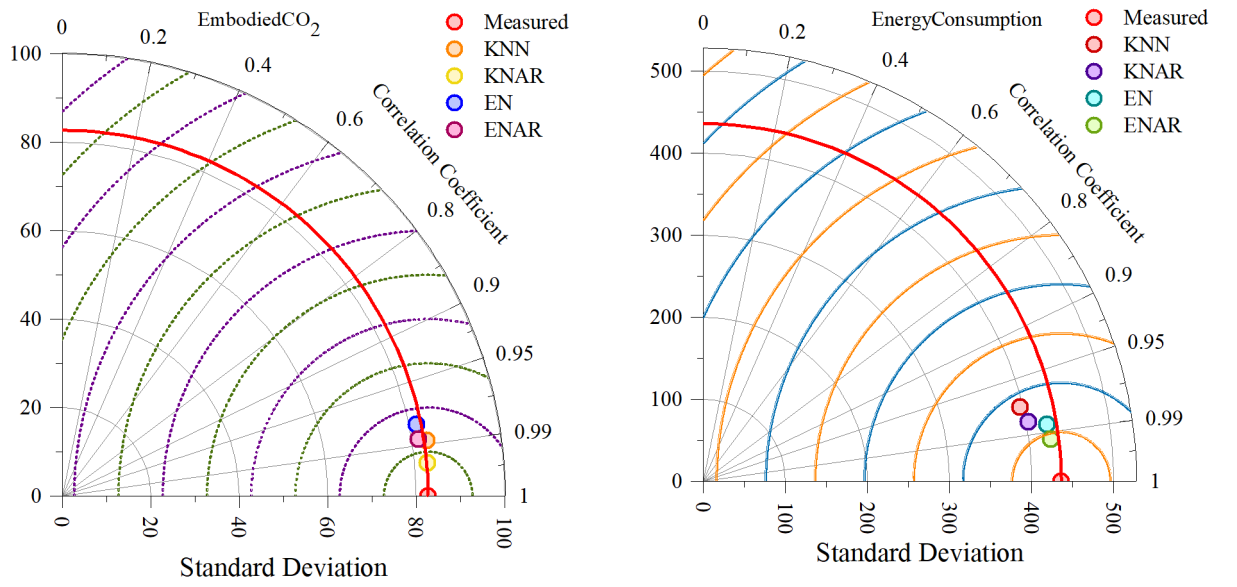


Figure 7: The Taylor diagram of related models with measured value

4.1 Practical use of the model in real-life building and planning

The proposed predictive framework provides a data-driven decision-support tool for real-world applications in concrete production and sustainable construction planning. By accurately forecasting CO_2 emissions and energy consumption based on HPC mix compositions, the model enables:

1. Environmentally Conscious Mix Design: Engineers can identify and minimize high-emission ingredients (e.g., excess cement or superplasticizer) during the early design stage, aligning material selection with carbon footprint targets.
2. Energy-Efficient Manufacturing Planning: By predicting energy demands of specific mix designs, batch plants can optimize their production schedules, reduce energy peaks, and lower operational costs.
3. Compliance with Green Building Standards: The model helps project teams evaluate whether proposed concrete mixes meet environmental criteria defined by certifications such as LEED, BREEAM, or China's Green Building Evaluation Label.
4. Lifecycle Sustainability Assessment: When integrated into Building Information Modeling (BIM) or digital twins, the model contributes to estimating the embedded carbon and energy profiles of structures early in the planning process, aiding urban planners and policymakers in meeting climate mandates.

Ultimately, the model acts as a predictive sustainability lens through which building materials can be assessed, optimized, and selected, without trial-and-error or over-reliance on empirical tables.

5 Conclusion

Most of the manufacturing processes for HPC systems are critical in terms of CO_2 emission and energy consumption, which should be minimized to support the environmentally responsive construction industry. Correct prediction of such factors is highly important for the optimization process of production and in maintaining complete harmony with sustainability considerations and the EE of the process. This work is focused on investigating the most influential ML models and the most influential features that have a great effect on the accuracy of the prediction in CO_2 emissions and energy consumption during the manufacturing process of HPC. ML techniques, including KNN, ENR, and ARO, were used to create predictive models. These models were further refined with optimizers to enhance prediction accuracy and identify the best solutions. Additionally, RFE was employed for FS, ensuring that only the most relevant variables were used to make precise predictions. The best performance for the estimation of energy consumption was given by the ENAR model, yielding an R^2 value of 0.986 and an RMSE of 52.626. The KNAR model performed best in estimating CO_2 emission, giving an R^2 value of 0.992 and an RMSE of 7.573. Therefore, the relevant features that most influenced the performance of the models were cement and superplasticizer. These were important in enhancing the predictive accuracy of energy consumption and CO_2 emissions for the models. The results have shown how important it is to consider the optimization of models along with input features in enhancing sustainability within HPC manufacturing. There are several drawbacks to utilizing ML to anticipate CO_2 emissions and HPC energy use. These include data quality and availability, as erroneous or inadequate datasets might impair model accuracy. Furthermore, it is challenging to generalize forecasts due to the intricacy of HPC systems and their diverse operating environments. Complex interactions between variables may be difficult

for ML models to capture, which might result in overfitting or underfitting. Lastly, scalability and real-time use in dynamic industrial contexts are limited by the computational cost and time needed to train big models on complicated datasets.

Acknowledgement

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