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IDENTIFICATION OF THE DAMAGE TYPES FOR REINFORCED CONCRETE USING CNN MODELS

DOLOČITEV VRSTE POŠKODB ARMIRANEGA BETONA Z UPORABO CNN MODELOV

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Monitoring reinforced concrete structures makes it possible to prevent their further destruction, thereby significantly reducing the cost of their maintenance. Machine learning excels in precisely identifying and classifying various types of damage. The convolutional neural network, constructed based on deep learning principles, could precisely identify and categorize many occurrences of deterioration in pictures of reinforced concrete. The evaluation of the convolutional neural network's performance in this study included assessing parameters such as accuracy, efficiency, and loss, and validating the enhanced architecture. Using a database that included 3200 images, it was found that a CNN containing 3 convolutional layers, 3 pooling layers, 1 rectified linear unit, filter 32/64/128, kernel size 4×4, and dropout 0.5 shows the best values in Accuracy (71.67–84.38%), Efficiency (14.4–2370 s), and Loss (0.99). The best results this CNN shows in the estimation of the combination of damages (crack + rebar exposure): Accuracy – 98.81%; Efficiency – 3945 s; Loss – 0.57. So, the use of the convolutional neural network model enables the identification of various forms of damage and the automation of the assessment of surface conditions in reinforced-concrete structures.

Keywords: convolutional neural network, reinforced concrete, damage detection, image recognition, structural health monitoring, deep learning

Stalno opazovanje armirano-betonskih konstrukcij omogoča preprečitev njihovega propadanja s čimer se znatno zmanjšajo stroški njihovega vzdrževanja. Strojno učenje omogoča natančno prepoznavanje in razvrščanje različnih vrst poškodb. Konvolucijska nevronska mreža (CNN; angl.: convolutional neural network), zgrajena na podlagi načel globokega strojnega učenja lahko natančno prepozna in kategorizira številne pojave propadanja na fotografskih in video posnetkih armiranega betona. V tem članku avtorji opisujejo študijo v kateri so ocenili delovanje konvolucijske nevronske mreže z oceno parametrov, kot so natančnost, učinkovitost in izgube, ter validacijo izboljšane arhitekture. Z uporabo baze podatkov, ki je vključevala 3200 posnetkov so ugotovili da CNN, ki vsebuje 3 konvolucijske plasti, 3 združevalne plasti, 1 rektificirano linearno enoto, filter 32/64/128, velikost jedra 4×4 in izpad 0,5, kaže najboljše vrednosti v natančnosti (od 71,67 do 84,38 %), učinkovitosti (od 14,4 do 2370 s) in izgubah (0,99). Najboljše rezultate CNN kaže pri ocenjevanju kombinacije poškodb (razpoka + izpostavljenost armature): natančnost – 98,81 %; učinkovitost – 3945 s; izguba – 0,57. Uporaba konvolucijskega modela nevronske mreže torej omogoča identifikacijo različnih oblik poškodb in avtomatizacijo ocenjevanja površinskih stanj v armirano-betonskih konstrukcijah.

Ključne besede: konvolucijske nevronske mreže, armirani beton, zaznavanje poškodb, slikovno prepoznavanje, spremljanje in ocena "zdravja" konstrukcij, globoko strojno učenje

1 INTRODUCTION

Reinforced-concrete structures undergo various forms of destruction over time and exposure to physical stress. If the structural issues are not promptly rectified, they possess the capacity to give rise to significant safety apprehensions by propagating flaws over the full duration of the structure's infrastructure.[1] Reinforced concrete may deteriorate due to many processes, with corrosion induced by the intrusion of chloride or concrete carbonization being the most prevalent.[2] Minor cracks lead to below-average performance, whereas severe fissures lead to total structural collapse.[3] A crack is a crucial factor in assessing the state of existing structures and infrastructure.[4] Spalling is the term used to describe the peeling of the concrete's surface without revealing the underlying rebars.[5] This issue not only impacts the visual aspect but also has adverse consequences on the structural integrity and functional excellence of infrastructure assets.

This widespread kind of deterioration impacts the strength and capacity to be maintained of concrete.[6] To avoid harm and system failures, security measures may be implemented via rapid assessment and detection.[7] However, the efficacy of human visual inspections is often limited by the level of training provided to the inspectors.[8,9] Furthermore, it may not be ideal for areas where the needed infrastructure is not easily available. Critics typically point out the inefficiency of human visual assessment, citing its high costs, lack of security, limited precision, and unreliable nature.[10] Hence, to en-

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hance the effectiveness and impartiality of evaluating damage, it is essential to devise an identification methodology that optimizes the precision in distinguishing different forms of damage to reinforced concrete.

Machine learning refers to the capacity of intelligent systems to enhance their performance by acquiring knowledge and improving their capabilities via the analysis of substantial amounts of data.[11] Scientists have suggested a technique for monitoring the condition of buildings that uses artificial intelligence and neural network modeling to quantify the degree of structural decay.[12] The author used machine-learning techniques to compute the distribution of steel weight reduction in reinforced-concrete beams. This data could potentially be used in the future to forecast the bending load. The researchers used eight machine-learning approaches to determine the mechanism of seismic collapse in reinforced-concrete shear walls. The shear capacity of steel fiber-reinforced concrete beams was predicted using eleven machine-learning methods.[13] Computer vision technology enables the operation of facility structures in a contactless, long-range, fast, inexpensive, and non-disruptive way.[14] Lately, scientists have developed computer-vision algorithms to detect and examine various forms of RC damage.[15,16]

Machine learning often employs algorithms to classify photographs and recreate public constructions.[17–19] The list comprises support vector machines, random forests, artificial neural networks, principal component analysis, clustering analysis, self-organizing maps, and deep learning.[20,21] In the past, the categorization of objects has mostly relied on color and texture as dependable indications, since these characteristics effectively represent the outward characteristics of the things.[22–24] Feature extraction is a method used to identify the distinct characteristics of pictures.[10] Furthermore, these techniques extract the characteristics of the photographs and then assess the presence of any damage, which is unavoidably impacted by hand annotation.[6] Therefore, using deep-learning methods[25–27] is beneficial.

Deep-learning models enable computers to automatically acquire and extract knowledge, in contrast to previous techniques. Supervised learning techniques rely on these traits, whereas deep-learning approaches eliminate the need for human feature engineering.[14] Convolutional Neural Networks (CNNs) have intricate structures and use convolutional processes, which significantly boost their exceptional accuracy in the domain of image recognition.[28] The primary objective of CNN is to reduce reliance on past data and human picture labeling, hence enhancing the efficiency of feature extraction. CNN is capable of autonomously identifying certain traits without relying on human knowledge or abilities, unlike earlier approaches. However, it gains the capability to recognize and distinguish these attributes from the dataset that was used for its training.[30] Hence, CNN can accurately identify and categorize pictures, irrespective of their dimensions, locations, and orientations.[30] These damage qualities provide significant obstacles that need the use of image identification or detection.

According to authors,[31] deep learning has difficulties in accurately identifying damage in civil engineering structures because of their unique characteristics and the variations in surface colors. Enhancing the precision of detection is a critical concern that must be given priority in classification algorithms. By optimizing the CNN's architecture through systematic hyperparameter tuning (e.g., kernel size, layer depth) and incorporating regularization techniques like dropout, the model's accuracy in damage identification can be significantly improved. This approach aligns with established CNN design principles for feature extraction in structural images.[28,32] Previous studies have used several architectures of CNNs.

Authors classified various concrete damage pictures that may occur under different conditions.[6] They performed tests to assess the effectiveness of several tactics to enhance the reliability of their suggested approach. This work employs four prevalent forms of reinforced concrete deterioration, including cracks, efflorescence, rebar exposure, and spalling, to enhance the precision of detecting various damage categories.

The main goal of our research is to develop a CNN model that would allow an accurate prediction of various types (as well as their combinations) of damage to reinforced concrete. The main objectives of our research are: selecting a data set of damage images and dividing it into a test set, validation set, and training set; selection of different CNN models that would differ in the number of convolutional layers, pooling layers, rectified linear units, filters, kernel size, hidden layer neurons, and dropout; development of a research plan that would include assessment of parameters such as Accuracy, Efficiency, Loss using developed CNN models to assess single and combined damage to reinforced concrete.

2 EXPERIMENTAL PART

Figure 1 shows a flowchart of the experimental part of this study.

The main method in this study is the use of a CNN-based structure for building the model. Subsequently, the model undergoes training and validation to precisely identify photographs that exhibit signs of damage to reinforced concrete. The CNN was primarily designed to effectively capture the spatial hierarchies and patterns within images by leveraging local and global feature extraction. **Figure 2** exhibits a used dataset. The shown images depict cracks, salt deposits, and the visibility of reinforcing bars. The dataset comprises 3200 images of reinforced concrete damage, evenly distributed across four categories: crack (800 images), efflorescence (800 images), rebar exposure (800 images), and combined damages (800 images, e.g., crack + rebar expo-

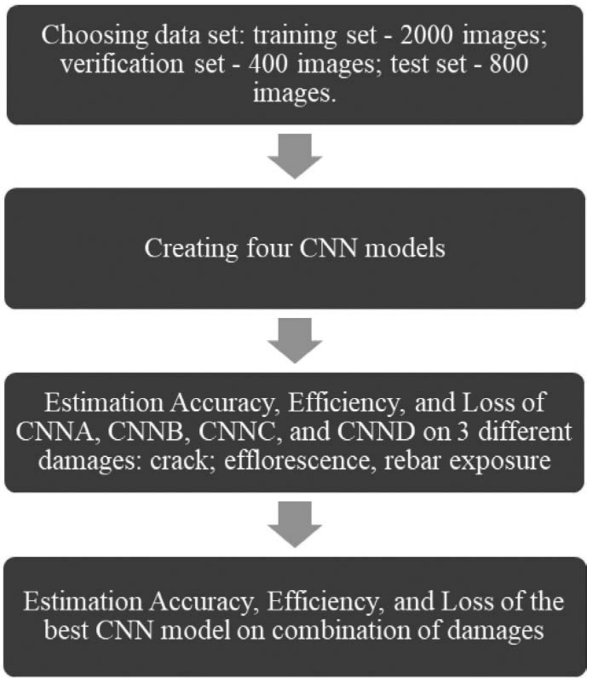

Figure 1: Flow-chart of the experimental part

sure). These images are split into training (2000 images), validation (400 images), and test sets (800 images).

The main purpose of the camera and picture data is to serve as a visual tool for identifying different forms of damage and conducting condition assessments. This research utilizes the image sensor of a digital camera, which can gather visual data via human manipulation. The device's remarkable resolution, compact size and convenient mobility make it perfect for efficiently assessing surfaces and scanning tight spaces to analyze the condition of different facilities in a limited area.

A total of 3200 images of damage to RC buildings were taken in educational institutions, laboratories, student dorms, sports venues, and places where students have meals (**Figure 2**). The aim of training and testing was to use certain data sets from the whole group. The hyperparameters of the CNN are fine-tuned to provide an effective model for identifying and classifying the damage to reinforced concrete. In the end, a meticulous selection process was used to get photographs that illustrate four distinct categories of damage. Subsequently, these photographs were included in the models to expedite the process of comparing and distinguishing different types of damage. To enhance the model's performance, it is feasible to create a deep network architecture that is suitable for the picture dataset. Additionally, it necessitates doing several iterations and conducting testing. This research utilizes a dataset including 3200 photographs that have experienced degradation. These photographs are used for training, validation, and testing. By optimizing the parameters of the CNN, such as training the model, adjusting the parameters, and evaluating its performance, it is possible to develop models that can accurately recognize different types of damage in photographs. To optimize the model's performance, the parameters are fine-tuned using the CNN options (CNNA, CNNB, CNNC, CNND) on a dataset consisting of training and testing pictures. The study examines four distinct neural network architectures, detailed in **Table 1**, to identify three common types of damage in reinforced concrete. The experimental results demonstrate that en-

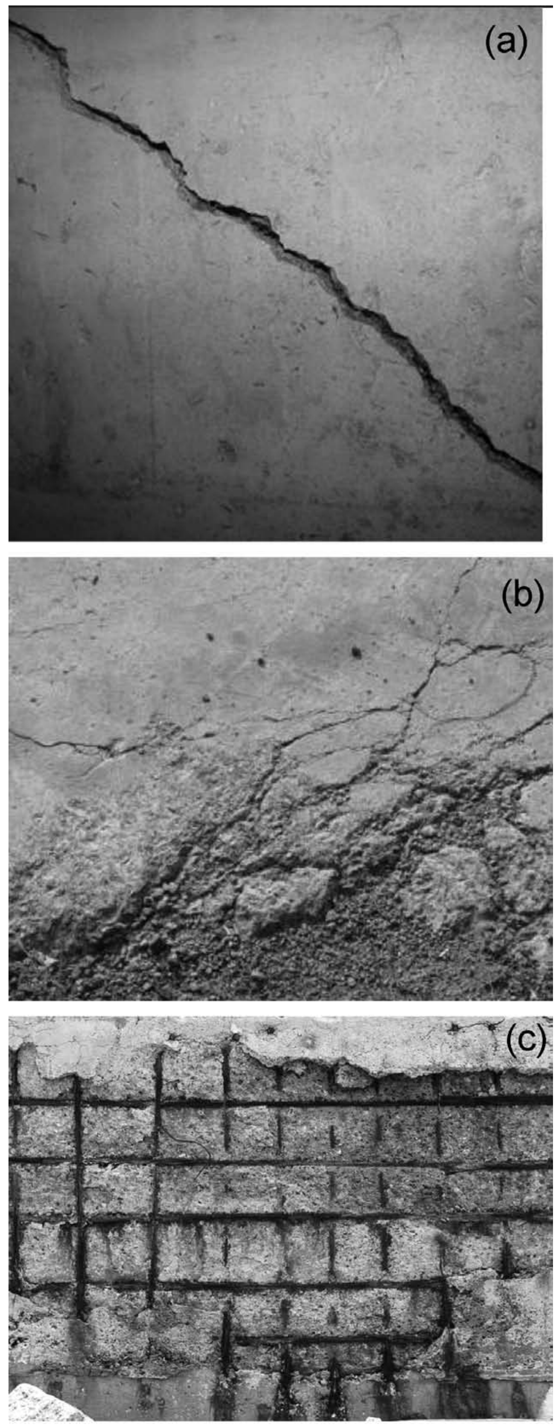

Figure 2: Three classes of damage: a) Crack, b) Efflorescence, c) Rebar exposure

hancing the model's capacity (by increasing filter dimensions and quantity, deepening convolutional layers, expanding hidden layer neurons, and incorporating dropout) significantly improves its ability to process and classify diverse image variations.

Table 1: Four architectures based on CNN.

Parameter	CNNA	CNNB	CNNC	CNND
Convolutional layer	1	3	3	3
Pooling layer	1	3	3	3
Rectified linear unit	1	1	1	1
Filter	32	32/64/128	32/64/128	32/64/128
Kernel size	6×6	6×6	4×4	4×4
Hidden layer neuron	1500	500/1000	500/1000	500/1000
Dropout	–	–	–	0.5

Table 1 outlines four distinct CNN architectures, each tailored for various tasks. CNNA offers simplicity with only one convolutional and pooling layer, utilizing 32 filters and a 6×6 kernel size. Conversely, CNNB, CNNC, and CNND employ three convolutional and pooling layers, enabling more complex feature extraction. CNNB's filter count varies between 32, 64, and 128, while CNNC and CNND share this variability. CNNB and CNND use 6×6 kernels, while CNNC opts for smaller 4×4 kernels. In terms of hidden layer neurons, CNNA uses a single hidden layer with 1500 neurons, while CNNB, CNNC, and CNND employ hidden layers with neuron counts varying between 500 and 1000. Dropout regularization is absent in CNNA, CNNB, and CNNC, but CNND integrates it with a 0.5 rate, reducing the overfitting risk during training. This diversity in architecture allows for flexibility in addressing different machine-learning challenges. CNNA's simplicity may be advantageous for straightforward tasks, while CNNB, CNNC, and CNND's deeper architectures suit tasks requiring intricate feature hierarchies. The choice of architecture depends on the specific requirements of the task at hand, such as dataset size, complexity, and computational resources.

Evaluating classifiers relies heavily on the quality of the predictions and involves comparing different supervised learning methods by analyzing the accuracy of trained classifiers on a certain dataset.[33] The model training process employed cross-entropy loss, a standard choice for classification tasks, to optimize performance.[34]

3 RESULTS

The usefulness of the training model, mainly in spotting types of image damage, can only be checked using a proper measurement technique. The evaluation approach measures the model's accuracy by comparing the forecasted information with the actual information. **Figure 3** highlights the outcomes obtained by analyzing four RC damage photographs using four different models, according to different kinds of criteria. To measure supervised learning techniques, accuracy is the most important factor. The accuracy measures how many right predictions there were for each class among all the predicted classes. Any time the model accurately identified helpful details in a picture, it was labeled a true positive (TP), while occasions when the model did not see anything in an empty image were classified as true negatives (TN). The model makes a false positive when it classifies an object present in an image as something important, although it is not actually that. If the model fails to even notice an item of interest that is in the image, it is called a false negative (FN). Here, it is evident from this study that the test set, training set, and validation set were evaluated accurately and precisely.

Table 2 shows the confusion matrix for the CNND model's performance in classifying the combined damage type "crack + rebar exposure" (Class 2).

Table 2: The confusion matrix

Actual \ predicted	Crack + rebar exposure	Other damage types
Crack + rebar exposure	197 (TP)	3 (FN)
Other damage types	2 (FP)	598 (TN)

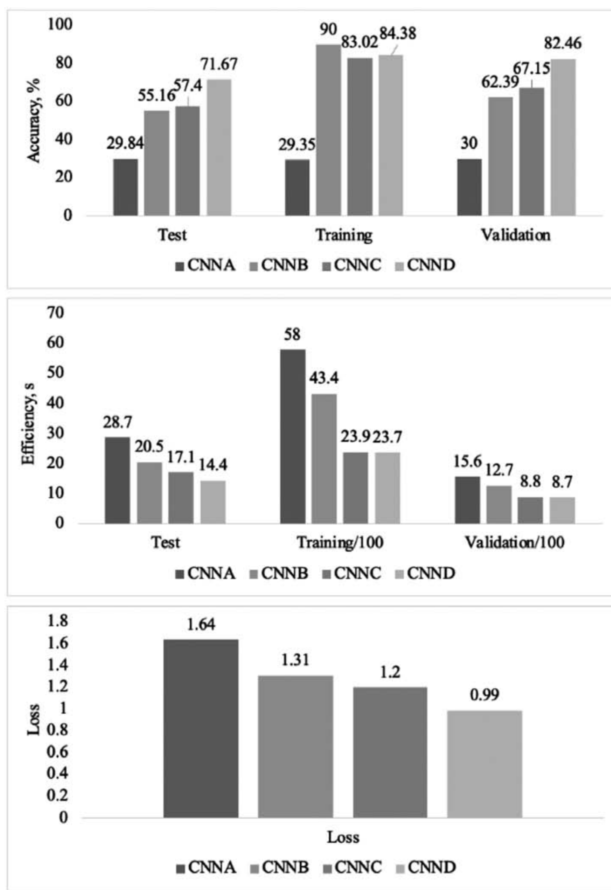

Figure 3: Test results: a) Accuracy; b) efficiency; c) loss

The confusion matrix demonstrates the CNND model's high precision in identifying "crack + rebar exposure" damage, with 197 true positives (TP) and only 3 false negatives (FN). The 2 false positives (FP) and 598 true negatives (TN) reflect minimal misclassification of other damage types (e.g., efflorescence or single damages) as the target class.

Efficiency is the measure of the time required for the model to complete the training process for picture identification. The use of a CPU slows down the process of calculations more than doing the same work with a GPU. The use of a GPU in detecting tasks will lead to faster results. According to the results of the experiments, if the filter is made 4×4 in size, the model trains much faster, even though there is little difference in accuracy. On the other hand, the progress discovered cannot be considered widely significant. CNND's computational cost is the cheapest, as it takes 14.4, 2370, and 870 s for testing, training, and validation, respectively. This research compiled a dataset consisting of four prevalent types of damage images seen in reinforced concrete: cracks, efflorescence, and rebar exposure. A total of 3200 photographs depicting instances of reinforced-concrete damage were acquired, with an equal distribution of 800 images for each category of damage. Each experiment utilizes two distinct sets of pictures that have been degraded for separate categories. The upgraded CNND's ability to identify two types of damage is evaluated using three separate image pairs. Class 1 exhibits a graphical depiction of a crack and efflorescence. Class 2 provides a graphical depiction of the presence of cracks and the exposure of rebar. **Table 3** in Class 3 displays a graphic depiction of a fracture and the visibility of the rebar.

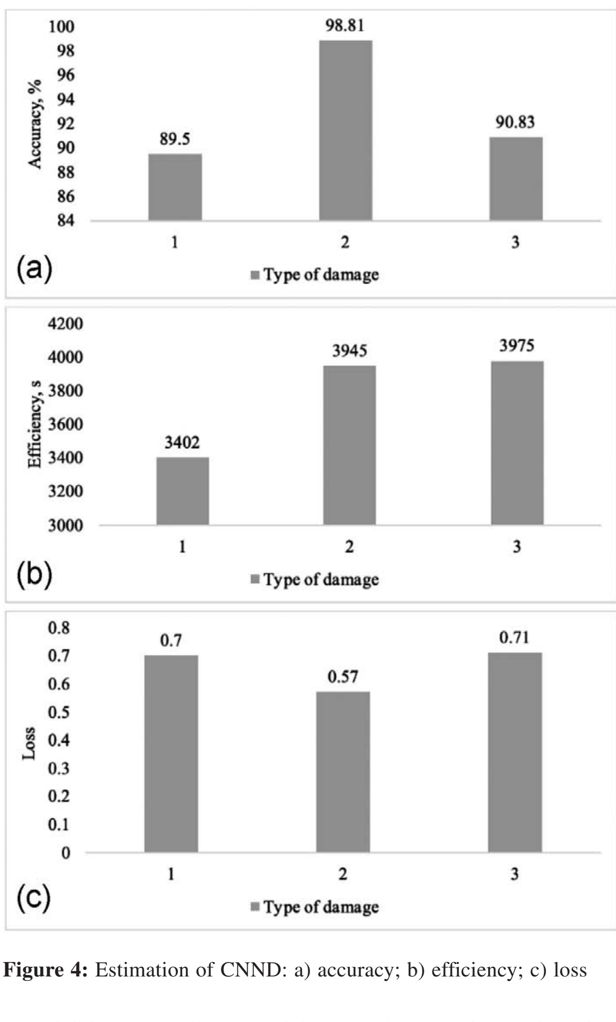

Figure 4: Estimation of CNND: a) accuracy; b) efficiency; c) loss

Table 3: Combination of reinforced concrete damage images.

Type of damage	Combination of damage
1	Crack + efflorescence
2	Crack + rebar exposure
3	Efflorescence + rebar exposure

Figure 4 demonstrates that CNND obtains the highest degree of identification performance for Class 2, with an outstanding accuracy of 98.81 % and a loss of 0.57. The data suggest that the model had exceptional identification abilities in detecting crack and rebar exposure. The accuracy and loss for Class 1 and Class 3 exhibit a substantial degree of similarity.

To enable the independent detection of the condition of an RC facility, a highly efficient identification model is required. RC facilities provide the capability to inflict many forms of harm at the same time, allowing them to effectively carry out a diverse array of damage identification tasks. This research used a fusion of three remote sensing (RC) damage photographs to assess the effectiveness of Convolutional Neural Network-based Detection (CNND) in the field of multi-image recognition. The precision of CNND in detecting three types of reinforced concrete damage ranges from 89.5 % to 98.81 %. The loss experienced throughout this process ranges from 0.57 to 0.7, while the efficiency of the system is evaluated between 3402 and 3975 seconds. The model has shown its robustness in accurately detecting various types of damage and consistently generating positive outcomes. Each CNN hyperparameter serves a distinct purpose due to its abundance.

This article presents a summary of the main elements involved in the process of finding the hyperparameters of a CNN after the design and optimization of its structure. The CNN was trained and tested on many kinds of light damage. As the number of filters increases, a larger number of feature maps are produced. By isolating additional elements from the picture, it becomes simpler to determine the content of the image. Based on the results of this inquiry, it can be concluded that the filters with values of 32, 64, and 128 are the most suitable. As the kernel size decreases, the CNN becomes less capable of learning the characteristics of the picture. According to the results of this experimental study, it is recommended that identifying photos have dimensions of 4×4. The stability of the model is compromised when several kernel sizes of varying magnitudes or combinations are used.

An essential attribute of a CNN is the need for a substantial amount of training data to enhance the efficiency of the model. Deep neural networks often outperform conventional designs in terms of performance. The findings of this research indicate that models with many hidden layers, including an equal number of neurons, have somewhat greater accuracy in comparison to models with a single hidden layer. The picture data's quality is a crucial determinant in identifying damage and significantly impacts the model's performance.

Moreover, it is crucial to regularly train and assess the model to identify a suitable architecture that effectively collects visual data. Photogrammetric pictures of building surfaces provide essential information on the extent and severity of damage. Since classification tasks normally use complicated neural networks, this technique provides good training and detection times. Also, the process shows both speed and precision, which make it perfect for meeting the efficiency needed in building identification and condition assessment. All four categories in the CNND damage list prove its effectiveness in identifying different kinds of harm. CNND can carry out multiclass image recognition and object classification, proving its strong ability to obtain complex features. The model can mark down different forms of damage, for example, cracks, efflorescence, and when rebar appears. As a result, a precise evaluation of the extent, amount, whereabouts, and seriousness of damage can be obtained through an in-depth analysis of the picture against what an expert found.

4 DISCUSSION

The main goal of the CNNB architecture is to enhance feature extraction through a more focused approach. Studies suggest that deeper neural networks tend to capture more refined and discriminative features, which can significantly boost a model's performance.[35] In theory, deeper network structures often outperform shallower ones in feature representation. Previous research indicates that improving CNN performance in object recognition can be achieved by deepening the network architecture and applying optimization techniques.[7] Following this approach, CNNB enhances the CNNA's structure by adding more convolutional layers, pooling layers, and an extra hidden layer. Additionally, studies confirm that progressively doubling the filters in consecutive convolutional layers results in a higher number of feature maps, further improving feature extraction in the hidden layers.[36] This enables the retrieval of more relevant information from the supplied photos. Thus, CNNB augments the filter count to 64 and 128, while maintaining the other parameters identical to CNNA.

According to the authors,[29] reducing the size of the input sliding window decreases the ability of the CNN to learn visual attributes. As a result, this hurts the overall performance. Nevertheless, by reducing the dimensions of the sliding window, it becomes feasible to precisely determine the specific location of the affected region. Hence, CNNC modifies the dimensions of the filters in the original CNNB architecture, reducing them from 6×6 to 4×4, while keeping the number of layers and parameters the same. To mitigate the problem of overfitting in the fully connected layer, it is possible to use the dropout layer. The original architecture of the CNNC includes a dropout rate of 0.5, which is implemented by CNND.

The findings are compared to two research articles[37,38] that obtained similar accuracy on the well-recognized dataset.[39] The authors showcased the efficacy of neural architecture search (NAS) in identifying many actual defects in the CODEBRIM dataset. The researchers[40] examined the use of transfer learning in identifying bridge degradation by using the dataset[41] and employing deep learning models such as VGG16, Inception-v3, and ResNet50. The findings are compared and shown in **Table 4**.

Table 4: Comparison of model accuracy

Model	Accuracy, %	Reference
MetaQNN	72.19	Mundt et al.[40]
ENAS	70.78	Mundt et al.[40]
VGG16	88.00	Mundt et al.[40]
Inception-V3	89.00	Mundt et al.[40]
ResNet50	89.00	Mundt et al.[40]
CNND	98.81	This study

Table 4 presents a comparative analysis of model accuracies across various architectures. MetaQNN achieves 72.19% accuracy, as referenced in Mundt et al.,[40] while ENAS follows closely at 70.78 %.[40] VGG16 achieves 88.00% accuracy, as noted in Mundt et al.,[40] indicating its strong performance. Inception-V3 and ResNet50 both attain an accuracy of 89.00% as cited in Burhsh et al.,[41] showcasing their effectiveness in image-recognition tasks. CNND, proposed in this study, surpasses all others with an impressive accuracy of 98.81%. This exceptional performance underscores the efficacy of CNND for the specific task under consideration. Each model's accuracy reflects its ability to accurately classify or predict outcomes based on the given dataset. While MetaQNN and ENAS offer competitive performances, VGG16, Inception-V3, and ResNet50 demonstrate superior accuracy, especially in complex tasks. CNND's substantially higher accuracy suggests its potential for applications requiring precise and reliable predictions, making it a notable contribution to the field.

While advanced architectures like ResNet-50 and Inception-V3 typically outperform simpler CNNs in large-scale datasets, the superior accuracy of CNND (98.81 %) in this study may stem from task-specific optimizations. First, the limited dataset size (3200 images) and the homogeneous nature of the reinforced-concrete damage (e.g., cracks, rebar exposure) may favor shallow architectures by reducing overfitting risks. Second, CNND's tailored hyperparameters (e.g., 4×4 kernel size, dropout = 0.5) likely enhanced feature localization for small-scale defects, whereas deeper models might overcomplicate feature extraction for this specific task. Third, the study's focus on combined damage types (e.g., crack + rebar exposure) may benefit from CNND's explicit architectural constraints, avoiding redundant hierarchical features extracted by ResNet or Inception. However, further validation on larger datasets and ablation studies (e.g., freezing pretrained layers in ResNet) are needed to generalize these results.

Recent studies highlight advances in damage detection for reinforced-concrete structures using deep learning and sensor-based approaches.[42–44] These works collectively underscore the potential of integrating machine learning with emerging sensing technologies to enhance the precision and efficiency of structural damage assessment, aligning with the findings of our study on CNN-based damage classification.

5 CONCLUSIONS

The study employs a dataset comprising 3200 images depicting various forms of damage to reinforced-concrete structures, including cracks, efflorescence, and rebar exposure. The dataset is divided into training, validation, and testing sets. Four different CNN architectures (CNNA, CNNB, CNNC, CNND) are proposed and compared. These architectures vary in terms of the number of convolutional and pooling layers, filter sizes, kernel sizes, number of hidden layer neurons, and dropout rates. The CNN models are trained and fine-tuned using the dataset. The performance metrics evaluated include accuracy, efficiency (training time), and loss. The study demonstrates the effectiveness of the CNND model in identifying different types of damage in reinforced concrete structures. The CNND model achieves high accuracy (98.81 %) in detecting specific types of damage, outperforming other models and existing approaches. The study compares the accuracy of the CNND model with other approaches, including MetaQNN, ENAS, VGG16, Inception-V3, and ResNet50, showing superior performance. The study recommends specific CNN architectures and hyperparameters for efficient damage identification in reinforced concrete structures based on the findings from experimentation.

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Conflict of interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data availability

Data will be available on request.

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