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RESEARCH ARTICLE

# Skin cancer segmentation and classification by implementing a hybrid FrCN-(U-NeT) technique with machine learning

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## Abstract

Skin cancer is a severe and rapidly advancing condition that can be impacted by multiple factors, including alcohol and tobacco use, allergies, infections, physical activity, exposure to UV light, viral infections, and the effects of climate change. While the steep death tolls continue rising at an alarming rate, lack of symptoms recognition and its preventive measures further worsen the case. In this article, we employ the ISBI-2017 dataset to present an improved FrCN-based hybrid image segmentation method with U-Net to improve detection performance. This paper proposes a hybrid approach using the FrCN-(U-Net) image segmentation technique to enhance results compared to an advanced method for detecting skin cancer types, such as Benign or Melanoma. The classification phase is then handled using the R-CNN algorithm. Our model shows better performance in both training and testing accuracy than any other existing approaches. The results show that the combined method is effective in enhancing early disease diagnosis, which in turn improves treatment outcomes and prognosis. This paper presents an alternative technique for skin cancer detection, which can serve as a guide for clinical practices and public health strategies on how to lower skin-cancer-related deaths.

## I. Introduction

Skin disorders are among the most prevalent health conditions in humans due to the skin being the body's largest organ and its continuous exposure to environmental factors [1]. Skin disorders do not frequently create changes in the skin. Some skin disorders are unavoidable. There is no way to change your DNA or avoid developing an autoimmune disease, for example [2,3]. Most people are aware

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of skin cancer, although melanoma is a considerably more common kind. The American Cancer Society's annual report projected that in 2017, there would be approximately 87,110 new cases of melanoma, with up to 9,730 deaths attributed to the disease [4]. Malignancy, though less communal than other forms of skin malignance, is particularly dangerous because of its high potential for metastasis if not detected and treated promptly. Malignant cells is a type of skin malignance that is distinguished by uncontrollable melanocyte growth (the cells which gives the skin its tan or brown colour). Cancer arises when certain cells begin to multiply unchecked, forming malignant tumors that can invade and spread to other parts of the body. It is one of the most lethal forms of skin cancer, with a fatality rate of 1.62 percent [5,6]. Early detection of melanoma is crucial streamlines treatment and improves the patient's prognosis [7,8].

There are so similar skin lesions and normal tissues, it is difficult to tell them apart visually during a medical examination, which can lead to an inaccurate diagnosis. Melanoma skin lesions have proven easier to spot using dermoscopy throughout the last decade [9]. The majority of epithelial tissue is formed in the skin. Melanomas can appear anywhere on the skin, and they're more typical in some locations. It most typically affects female's chest and back. Melanoma may appear on the face as well as other regions of the body [10,11]. The risk of melanoma can be lowered by reducing your exposure to UV radiation [12,13].

Dermoscopy is the non-invasive image procedure that utilizes polarized light in order to magnify a skin lesion. It is Dermatologists must spend a significant amount of time and effort screening through dermoscopy images to acquire an appropriate diagnosis, that dermoscopy has higher diagnostic accuracy than obtained via visual inspection [14].

Therefore, dermatologists will profit from computerized automated diagnostic techniques for skin issues.

Cancer is affected by the unrestrained or abnormal development of cells in the subsequent tissues or more adjoining tissues. Cancer is caused by several reasons, including not limited to UV radiation, the weaker immune system, the family history of cancer, and so on. The irregularity of cell growth is utilized to diagnose both benign and malignant tumors.

Benign tumors or cancer-free tumors are often referred to as moles. Malignant tumors are identified and make threats to life. The skin's structure includes three main layers: the epidermis, which contains basal cells, squamous cells, and melanocytes; the dermis; and the subcutaneous tissue.

It is a variable that contributes to the formation of cancerous tissue. Skin cancers come in several forms, including Melanoma, Squamous_Cell_Carcinoma (SCC), and Basal_Cell_Carcinoma (BCC), each considered to be serious and potentially life-threatening. Additionally, there are various other skin conditions such as Melanocytic Nevus, Benign Keratosis, Actinic Keratosis (AK), Vascular Lesions, and Dermatofibroma, which, while not necessarily cancerous, are important to recognize and monitor [15]. Fig 1 indicates the Stages of Melanoma below:

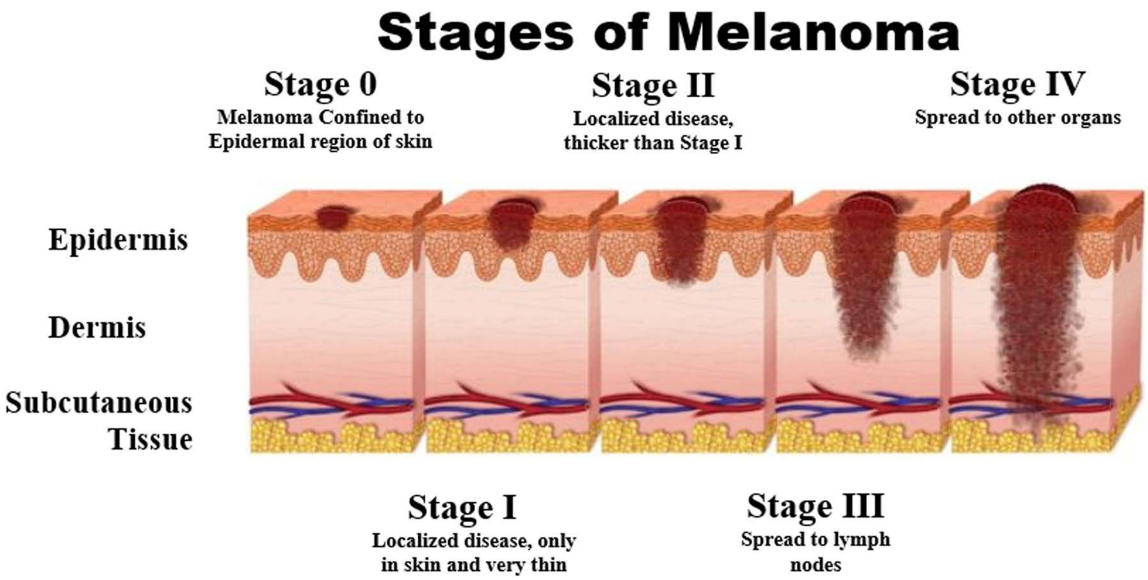


**Fig 1. Stages of Melanoma [ 16].**

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There are numerous kinds of skin cancer, Melanoma is the worst and can increase back even after surgical removal. Skin cancer is more common in Australia and the United States than everywhere else on the planet. Noise reduction in images is achieved through methods such as the Dull Razor approach, Gaussian filter, and Median filter. The melanoma could be alleviated by easy resection if it could be discovered at the beginning. Those who are diagnosed early have a survival rate of more than 95%, whereas those who are detected late have a survival rate of less than 20% [17]. For some time now, the categorization of skin lesions has been a hot issue in the machine learning industry. Physicians benefit from using automated lesion classification in their routine clinical practice, as well as having access to lifesaving diagnoses even while they are not in the hospital through mobile device apps [18].

Therefore, dermatoses must be detected and treated as soon as feasible. A subjective strategy is devised centered on visual perception of the lesion. There are used to remove characteristics from segmented images, two techniques are used: the “Asymmetry, Borders, Colors, Dermatoscopic Structures (ABCD)” method, and the “Gray Level Co-occurrence Matrices (GLCM)” method. The A.B.C.D Law is based on evaluating skin lesions according to their asymmetry, border abnormality, color deviation, and diameter. This law is extensively used for assessing lesions, both through dermatoscopy and with the naked eye, due to its straightforward and effective approach. The A.B.C.D. examination process is described below [19]:

- Asymmetry (A): The injury is separated into two vertical axes 90 degrees apart to get the lowest asymmetry score possible. Whether the lesion is proportioned or not is defined. If asymmetry is identified, one point is attached to each axis.
- Borders (B): Axes are utilized to split the lesion into eight slices to determine whether the lesion has abrupt boundaries. All segments with a well-defined boundary get an additional point.
- Colors (C): The lesion could be brownish, blue, dark brown, white, red, or black. These are created by vasculature and melanin concentrations; one point is assigned for each color detected.
- Dermatoscopic Structures (D): The lesion’s structures include dots, blobs, pigmentation networks, and unstructured patches. Each structure discovered on the lesion is worth one point.

The defined elements are weighted in equation (1) as follows:

$$TDS = (1.3)\,A + (0.1)\,B + (0.5)\,C + (0.5)\,D, \tag{1}$$

The Total_Dermatoscopic_Score (TDS) is used to evaluate skin lesions, with a score less than 0.475 suggesting that the lesion is probable benign. A TDS notch between 0.475 and 0.545 indicates a lesion that requires further examination, as it may have characteristics that are more concerning. It is regarded suspicious, and it is higher than 5.45 to be declared malignant.

This paper proposes a hybrid segmentation approach that combines two existing techniques, U-Net and FrCN. By employing the FrCN-(U-Net) hybrid algorithm, the approach achieves more accurate results compared to those obtained using each individual algorithm separately.

### A. Objectives

The leading objectives of this article are:

- To review and assess the current literature on image-based skin cancer classification and detection.
- To propose a hybrid methodology for integration and cataloging of skin cancer.
- To validate and verify the efficacy of the suggested method through enactment based comparisons with existing models.

### B. Contributions and paper organization

Many people are dying at an alarming rate due to a lack of understanding about how to recognize the signs of skin cancer or what preventive measures to take. Therefore, early detection is crucial to prevent the cancer from advancing and spreading.

This research integrates sophisticated machine learning algorithms and advanced image processing methodologies to systematically identify and classify diverse skin cancer types. The process begins with pre-processed dermoscopic images as the input. To enhance image quality, unwanted hair particles are removed from the skin lesions using a dull razor and Gaussian filtering techniques.

The Median filter is utilized to mitigate noise while maintaining the delineation of the lesion's boundaries. Given the pivotal role of color in skin cancer diagnosis, a color-focused k-means clustering approach is employed to categorize the disease based on its color attributes. Additionally, a comprehensive analysis of the lesions is conducted through the extraction of statistical and textural features, utilizing the ABCD rule and the Gray Level Co-occurrence Matrix (GLCM) to capture nuanced characteristics and patterns within the lesions.

In the experimental analysis, the research utilized the ISIC 2019 dataset, which comprises images representing eight distinct categories of skin lesions. These images were rigorously examined using a Multi-class Support Vector Machine (MSVM), which achieved an impressive accuracy rate of approximately 96.25%. The increasing global burden of skin cancer highlights the urgent necessity for early detection mechanisms, aiming to significantly enhance diagnostic accuracy and therapeutic efficacy. This research presents a methodology that combines MSVM classification with two robust feature extraction techniques, ABCD and GLCM, to ensure high accuracy. By incorporating a variety of eight skin cancer types, the approach provides a thorough and reliable classification.

Section 1 provides an introduction to the paper, outlining its objectives and scope. Section 2 delivers an extensive literature review, examining the current state of research relevant to the topic. Section 3 elaborates on the research methodology adopted for the study. Section 4 details the proposed methodology, highlighting its unique components and innovations. Section 5 presents a detailed analysis of the implementation results, offering insights into the performance and efficacy of the proposed approach. Finally, Section 6 synthesizes the principal findings and draws conclusions, summarizing the contributions and implications of the research.

## II. Review literature

There is various author work related to Skin Cancer Disease which is given below:

The usage of digital image processing to detect skin cancer is becoming increasingly common in the medical field. Skin cancer is responsible for a 1% increase in mortality per year. The lack of prediction in the initial phases of cancer is a major element in the number of fatalities caused by it. The results of this study will help in the development of novel ways for identifying tumors in their early stages. Preprocessing and segmentation are two of the most important steps in the method. Artifacts are not required to be eliminated using an upgraded approach that utilizes threshold and morphological operations, and the skin lesion is segmented in the second stage utilizing k-means with an Optimized Firefly Algorithm (OFA) technique to obtain high accuracy in skin lesion segmentation. The method uses input images from the Pedro Hispano (PH2) dermatological service and the International Skin Imaging Collaboration (ISIC) archive dataset, both of which are accessible online. Although ISIC and PH2 datasets have accuracy rates of 99.1% and 98.9%, modern methods, such as K-Mean with Particle Swarm Optimization (PSO), outperform them (Garg, Shelly, et al. [20]).

An innovative Computer-Aided Detection (CAD) system that combines deep learning techniques with mutual information measures has been developed for the identification and classification of dangerous skin lesions. The CAD system is structured around three core procedures: preprocessing, feature abstraction, and separation. In the preprocessing stage, the lesion image undergoes enhancement, segmentation, and filtering to isolate the Region of Interest (ROI). The succeeding stage focuses on feature extraction. Convolutional Neural Network (CNN) structural design, applied on ImageNet, is used to derive deep learning features from handcrafted attributes such as color, texture, and shape, which are aligned with the ABCD rule. Mutual Information (MI) measurements serve as fusion rules to integrate information from these different attribute types. The framework's architecture was assessed using the ISIC 2018 public dataset. Additionally, it is recommended to adopt a novel approach for adjusting evaluation metrics, particularly for datasets with diverse skin lesion types (Almaraz-Damian et al. [21]).

Melanoma skin tumor is the most dangerous type, with a substantially higher fatality rate compared to other cancers globally. Accurate melanoma diagnosis has prompted the development of various computer-aided techniques. Nevertheless, establishing a dependable system for precise melanoma detection remains a challenge due to the intricate visual characteristics and variability of nevi. Current systems either rely on traditional machine learning models that use manually selected features or on deep learning methods that learn features directly from entire images (Kumar et al. [22]).

The prevalence of malignant melanoma, an extremely serious kind of skin cancer, is growing every year. Detecting skin cancer from a skin lesion is challenging due to artifacts, low contrast, and similar visuals such as moles and scars. Multiple lesion detection algorithms are employed to distinguish skin lesions based on accuracy, efficiency, and performance parameters (Manne et al. [23]).

Skin disorders are a significant global health issue, contributing 1.79 percent to the overall burden of disease measured in disability-adjusted life years. To increase the precision of disease cataloging, a novel digital diagnostic system was developed. This system employs a Multi-Class Multi-Level (MCML) classification method, inspired by a "divide and conquer" strategy, to tackle research challenges. The method utilizes both customary machine learning and advanced deep learning techniques, incorporating improved noise removal methods (Hameed et al. [24]).

Computer vision systems for skin cancer detection have been proposed, with machine learning methods for disease classification. Features created on the ABCD dermatology criterion provide data on the position of a skin lesion based on static assets like geometry, texture, and color, making it an appropriate criterion for medical diagnostic systems that work with images (Vidya et al. [25]).

Melanoma is an aggressive and fast-spreading skin cancer, making it the most serious form and a major cause of mortality. Cataloging the phases of melanoma is a critical yet time-consuming process. The identification of malignancy during medical action largely depends on determining the phase of the cancer or the thickness of the tumor (Patil et al. [26]).

The global incidence of skin cancer is steadily rising, and early detection and treatment significantly improve patient survival rates. Accurate segmentation of skin lesion boundaries is essential for precisely identifying lesions in dermatoscopic images. A study introduced the Channel & Spatial Attention Residual Module CNN (CSARM-CNN) model, which is designed as an end-to-end system to automatically and efficiently segment skin lesions. A new attention module combines channel and spatial attention for each CSARM block in the model. Spatial pyramid pooling is used to create multi-scale images, achieving competitive performance on the ISIC 2017 and PH2 datasets with accuracy and specificity of 99.03% and 99.45%, respectively (Jiang et al. [27]).

Skin cancer has the greatest incidence rate compared to other types of cancer. A study used the Skin Cancer MNIST database to train a deep learning model integrating Multilayer Perceptron Neural Networks with Convolutional Neural Networks to classify pigmented dermatological lesions. The performance of Convolutional Networks was assessed, and the Grid Search with Cross Validation-based ensemble implementation was deemed accurate enough. Precision and F1-Score were 0.92 and 0.93, which is better than the performance of experts and similar studies (De Oliveira et al. [28]).

The varying appearance of lesions across individuals makes the task challenging. This challenge becomes considerably more complex when dealing with large amounts of image data. A deeper network architecture combined with less significant kernels was proposed to boost the network's ability to discriminate between different lesions more effectively (Yuan et al. [29]).

It is improved segmentation performance even further when purposefully consisting of color knowledge from many color spaces in the network training. These are attained a "Jaccard Index (JA)" of 7.65 on the 600 challenge analysis images, placing method first out of 21 final submissions in the competition by training through 2000 challenge training photographs. Table 1 outlines the results of implementing various lean principles, detailing their contributions and limitations.

### A. Problem formulation

Due to a lack of knowledge about its signs and preventative measures, death rates for skin cancer, a particularly severe type of cancer, have dramatically increased. A cancer diagnosis must be made early to prevent the disease from spreading. The background research projects cover machine learning-based image processing and cancer diagnostics [30].

After using a dull razor to remove any unwanted hair particles from the skin lesion, Gaussian filters are used to smooth the picture and median filters are used to reduce noise. Shape-based elements are among the essential aspects that are absent from the study's classification results. This might be addressed by using R-CNN to improve feature comparison and speed up the evaluation of big datasets. Also, dermoscopy images can be used for the diagnosis and classification of skin cancers based on sharp variations and fuzzy boundaries of the lesions. This study addresses the problems highlighted in the case study and in other related literature.

The current detection of skin cancer is mainly through traditional imaging techniques and manual examination, with limitations in accuracy and clinical skill set. These traditional methods still often fail to make very accurate distinctions between melanoma and benign melanoma. Hence, some means of improvement is necessary before attaining a reliable and exact solution. The present study is also necessitated by the very ill need for enhanced means of early skin cancer detection as these checks are essential in preventing the disease from worsening or lowering its mortality rates.

In order to improve detection accuracy, the research takes this requirement into account and suggests a novel hybrid picture segmentation method that combines the Fully Convolutional Networks (FrCN) and U-Net architecture. In the classification stage, we also use a Region-Based Convolutional Neural Network (R-CNN) technique to differentiate between benign and malignant patients. Our methodology is innovative because it incorporates these cutting-edge methods that, to the best of our knowledge, have not yet been extensively studied in the literature.

**Table 1. Assessment of lean principles application.**

| Source | Dataset | Classes | Methods used | Contribution | Limitations | Metrics Results |
|---|---|---|---|---|---|---|
| Garg et al. [20] | **ISIC 2017** | Segmentation | Segmenting Skin Lesions with K-Means Clustering and an Enhanced Firefly Algorithm | The developed approach is better and dominated the issue of a K-mean which is reached in nearby optima. | The author did not consider the color-based, shape-based, and texture-based features. | Not provided |
| Almaraz-Damian et al. [21] | **Ph2** | Classification | Asymmetry Borders-Dermatoscopic Structures and Mutual Information measurements | Mutual information measurement serves as the fusion rule, combining the most significant information from two distinct features. | The author did not work on the multiclass classification problem using two sets of features. | Not provided |
| Hameed et al. [24] | **ISIC 2017** | Classification | Multi-Class Multi-Level algorithm | The model helps the users and the skin specialists in the early detection of the skin cancer | The model is not successful in remote areas. | Accuracy: 92%, Sensitivity: 90%, Specificity: 88% |
| Vidya et al. [25] | **Unknown Data Set** | Classification | CNN | The execution time of the developed model is less in comparison to the other techniques (VGG-16, AlexNet, ResNet, and InceptionV4) | The author did not use the high image quality dataset. | Not provided |
| Patil et al. [26] | **ISIC 2017** | Classification | CNN with Similarity Measure for Text Processing (SMTP) | To achieve effective feature learning and test set performance, the author utilized an improved CNN architecture with SMTP as the loss function. | The developed model achieves a lower percentage of RRES and RAE. | Not provided |
| Jiang et al. [27] | **ISIC 2017** | Segmentation | Channel & Spatial Attention Residual Module-CNN | The model features a multi-scale input module, extracts image features using convolutional attention, and adjusts training parameters through a multi-label loss function. | The author used a small training dataset. | IOU: 75%, Dice Score: 78% |
| Yuan et al. [29] | **ISIC 2017 and Other Local Datasets** | Segmentation | Deeper network structures with smaller convolution kernels | The performance of the model is further enhanced by combining information with multiple color spaces. | The model is not able to accurately spot the area | IOU: 80%, Dice Score: 82% |

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By using the ISBI-2017 dataset, our study aims to demonstrate that this hybrid method not only provides a robust framework that can be applied in clinical settings for early and precise skin cancer diagnosis, but also improves detection accuracy. This study might revolutionise public health initiatives and clinical procedures, ultimately lowering the death rate from melanoma.

These difficulties highlight the need for an early warning system that can serve as a tool for early detection, categorise different skin conditions, and learn from pre-diagnosis outcomes. In order to solve this, we use the R-CNN approach for both training the suggested framework and identifying skin cancer.

## III. Research methodology

In the research methodology, the dataset includes a diverse array of skin cancer images. A substantial amount of information is collected to ensure high-quality results. One of the most difficult issues is acquiring skin cancer images, which are primary concerns to use the CNN method for training data.

Our study combines the advantages of Fully Convolutional Networks (FrCN) and U-Net for image separation to present a unique hybrid strategy for skin malignancy recognition and cataloguing. This hybrid technique improves accuracy and efficiency by utilising FrCN's precise segmentation skills and U-Net's robust feature extraction capabilities. To improve classification accuracy, the Faster R-CNN algorithm has been added to the model, enhancing its capability to differentiate between malignant and malicious melanoma. Compared to previous models, this combination of sophisticated segmentation and classification approaches provides a huge improvement. The updated publication will clearly define the innovation and unique contributions of our methodology, highlighting how our suggested method enhances the skin cancer detection and classification.

The technique begins with a set of dermoscopic images. The process involves three main steps: image input, preprocessing, and segmentation. Initially, the image is inputted, followed by preprocessing to reduce artifacts. The resulting filtered image is then used for segmentation, which is performed using a CNN.

Our study has a new way to divide images that puts together Fully Convolutional Networks (FrCN) and U-Net design, making it much better at finding skin cancer. The R-CNN technique is used to better distinguish between malignant tumors and non-malignant ones. We show our way is really good by using the ISBI-2017 data, and it works better than other ways. This research is really useful for finding bad tumors early and helping patients. Our work also helps people by giving a good way to find skin cancer, and could help make tools for doctors to use every day. Fig 2 illustrates the Schematic of the Skin Cancer Detection Technique [31].

**Step 1:** Initially input is taken for generating output based on research methodology.

**Step 2**: After getting the data, preprocessing is applied to the raw data to remove the noise and artifact from it.

**Step 3**: The next step is data reduction, where a large volume of data is transformed into the desired format.

**Step 4**: In this step, the segmentation technique is applied to data:

1) Segmentation: In segmentation, the goal is to locate the skin lesion's boundary within a dermoscopic image and identify the area of interest. This is prepared by linking every pixel in the spitting image to a relevant attribute [32,33].
2) Feature Extraction: The abstraction of characteristics is often considered the most crucial phase in the categorization process. Feature extraction is a sophisticated technique aimed at deriving critical attributes from an input dataset to enable advanced computations, such as detection and identification. This process is essential for optimizing resource utilization by reducing dimensionality while ensuring that significant and pertinent information is retained. It removes all the redundant data from the data set [34,35].
3) Classification: Convolutional_Neural_Networks (CNNs) are a deep learning approach tailored for handling complex, multi-class problems, distinct from Support Vector Machines (SVMs). CNN is an incredibly precise way to implement. Decision planes are used to categorize objects, and this approach is mostly founded on this concept. It defines the criteria for making decisions, and as a function, it has capability control. Following feature extraction, a classification technique is applied to filter and select the most relevant data from the dataset [36,37].

**Step 5**: In this last step, the final required outcomes are achieved effectively.

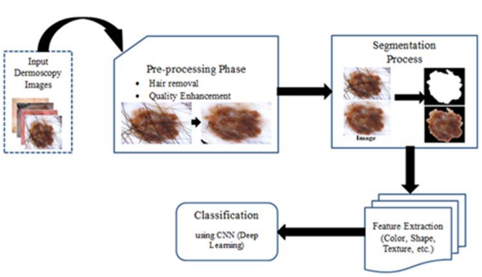


**Fig 2. Schematic of the skin cancer detection technique.**

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### A. Algorithm used

Following are the major algorithms that are used in the proposed methodology.

1) FrCN: To enhance pixel-wise accuracy in skin lesion segmentation, the FrCN approach utilizes full-resolution features for each pixel within the input data. This is achieved by eliminating subsampling layers from the network, allowing the convolutional layers to thoroughly capture and interpret the spatial details present in the input image.

2) U-Net: U-Net is a sophisticated CNN architecture, optimized with minimal modifications to efficiently classify and localize infections in biological images.

3) R-CNN: The R-CNN series is constructed on the principle of region recommendations. Region suggestions are used to locate elements inside an image.

The approach proposes to use the trio of algorithms, from Fully Convolutional Networks (FrCN), U-Net architecture for segmentation, and Region-Based Convolutional Neural Networks (R-CNN) for classification. Despite their respective accuracies in detection, the combination may come at a cost in terms of greater computation expense and complex developing time.

To do this, we analyzed the computational workload of each of the algorithms used in the framework. For FrCN and U-Net architectures, with their convolutional nature, complexity results in $O(n^2*k^2)$, where n is the dimension of input images and k is the kernel size. Though complex, their allowance for finer segmentation makes them very essential in obtaining accurate diagnosis. On the other hand, R-CNN with its region proposal network contributes to complexity of $O(N^2)$ for each N regions and thus is computationally costly for larger datasets.

In performance achievement, inferences were drawn on model pruning, parameter tuning, and hardware acceleration with GPU computation to save upon time taken and memory footprint. The utmost care was taken to ensure a trade-off between effectiveness and computational efficiency to make it practically applicable in a clinical mindset.

The analysis allows our study to shift towards a more practical incorporation of, on one hand boosting accuracy levels and on the other addressing efficient computational methods for real-life implementation of the framework.

### B. Segmentation technique

In general, CNNs are composed of two critical components that enable pixel-level classification for the segmentation technique. The subsampling and convolution layers are a first part. Convolutional layers extract deep features from an input image using filters of various sizes, while subsampling layers reduce the size of the resulting feature maps [38]. Subsampling does increase the robustness of the classifier in an image-wise classification job (such as conventional image classification using the CNN), as it decreases feature redundancy, minimises overfitting, and reduces the time of computation [39–41]. Subsampling reduces the spatial resolution of the input image during pixel-by-pixel segmentation. This is followed by upsampling layers and a softmax classifier, which uses the refined pixel attributes to categorize each by means of either a lesion or soft tissue pixel. To address the loss of pixel details due to image size reduction, modern deep learning segmentation methods employ advanced techniques such as bilinear interpolation, atrous convolution, upsampling, deconvolution, and decoding [42,43]. Additionally, post-processing techniques like Pixel-wise Classification (PI) or Conditional Random Fields (CRF) are often used to further refine segmentation boundaries [44,45].

This study introduces the FrCN-(U-Net) algorithm, which maintains full-resolution pixel features by removing subsampling layers. By integrating U-Net with FrCN, the hybrid model enhances performance, leveraging U-Net's architecture to address key issues and capture both contextual and localized features. Each pixel is treated as a distinct training sample, enabling detailed feature extraction for every pixel in the output image through convolutional layers.

### C. Faster R-CNN

The phrase faster refers to the evolution of Fast R-CNN, which produces results more quickly. Fast R-CNN, which is obtained from R-CNN, generates region recommendations prior to convolutional layers. This particular process is said to result in decreased performance when working with large photos.

Faster R-CNN (Ren et al., 2016) [46] addresses performance issues by integrating a Region Proposal Network (RPN) layer, thereby eliminating the need for pre-generated region proposals. The Region Proposal Network (RPN) is a fully convolutional network that simultaneously predicts both the boundaries of an object and its associated score. The computation of RPNs is developed to occur after the phase of feature extraction. As a result, CNN features map serves as an input to the RPN, which generates collection of the regions with projected scores. Fig 3 depicts the Faster_R-CNN's block diagram.

The Faster_R-CNN framework is structured with an input layer, a series of convolutional layers for feature extraction, a fully connected layer for high-level reasoning, and an output layer for generating final predictions.

## IV. Framework of the methodology

### A. Dataset used

The suggested segmentation approach is evaluated using a dermoscopy database in the implementation. The database is the "Skin Lesion Analysis Towards Melanoma Detection" dataset from the ISIC 2017 and 2018 competition.

The dataset, available over and done with the International Skin Imaging Collaboration (ISIC), features 8-bit RGB dermoscopy pictures with dimensions ranging from 540x722 to 4499x6748 pixels. It contains 2,000 images for training, as well as 600 and 150 images for testing and validation, respectively [36,47].

The proposed model was evaluated using two distinct sets of dermoscopic skin lesion data to assess its performance through simulation.

1) The ISIC-2017, or International Skin Imaging Collaboration: This data set includes studies for melanoma detection in addition to dermoscopic pictures of skin lesions [48]. During imaging, dermoscopy removes the skin's surface reflection [49].

2) International Skin Imaging Collaboration (ISIC-2018): Over 10,000 dermoscopic SL images in this collection may be used for research and medical diagnostics [50–52]. Skin Lesions have been categorised and documented by well-known SC experts.

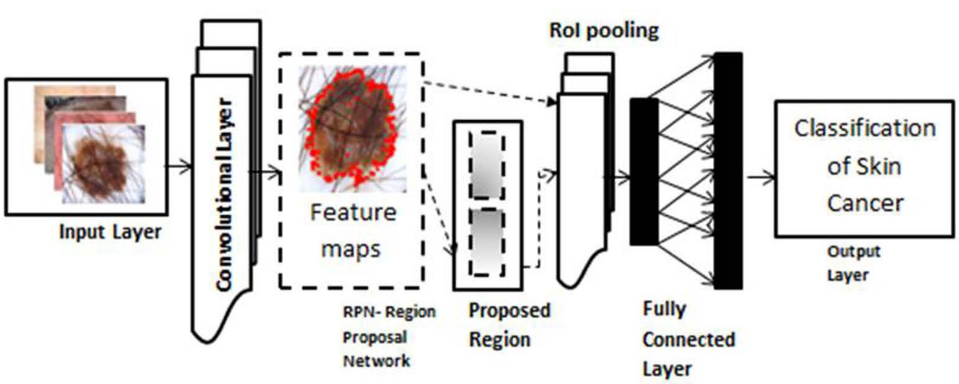


**Fig 3. Schematic representation of Faster_R-CNN architecture.**

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## B. Proposed methodology

***Step 1:*** An image is fed into the CNN model as input. CNN allocates significance to different objects in the image and is capable to distinguish one from the other.

***Step 2:*** Preprocessing is the second critical stage in transforming raw data into consistent data. The primary purpose of preprocessing datasets is just to improve actual medical images by eradicating artefacts such air bubbles, noise, and artefacts prior to image acquisition. To achieve a high classification value, noise, veils, hairs, stamps, and artefacts were eliminated from the photos. The method enhances image quality by modulating pixel intensity values through thresholding techniques and employs morphological operations to effectively eliminate hair artifacts from dermoscopic images. In a morphological process, optimal thresholding is used to reduce artefacts, and a structural element disc is used to reduce artifacts.

The following formulae calculate the probability of a pixel value:

$$\mathrm{Prob}\,(Z) = \mathrm{Prob}_1.\mathrm{pdf}_1\,(Z) + \mathrm{Prob}_2.\mathrm{pdf}_2\,(Z)$$

$$\Rightarrow \mathrm{Prob}1 + \mathrm{Prob}2 = 1 \tag{2}$$

$$\mathrm{pdf}_1\,(Z) = \text{Probability Density Function of BP} \tag{3}$$

$$\mathrm{pdf}_2\,(Z) = \text{Probability Density Function of OP} \tag{4}$$

Given an initial threshold value, denoted as "Th," pixels with values less than or equal to "Th" are classified as background, whereas those with values exceeding "Th" are identified as part of the object.

$$\mathrm{fun}\,(x, y) > \mathrm{Th} \rightarrow (x, y) \in \mathrm{obj} \tag{5}$$

$$\mathrm{fun}\,(x, y) \leq \mathrm{Th} \rightarrow (x, y) \in \mathrm{back\_ground} \tag{6}$$

Er1: An error occurs if a background_pixel (BP) is mistakenly classified.
Er2: An error occurs if an object_pixel (OP) is incorrectly classified.

$$\mathrm{Er}_1\,(\mathrm{Th}) = \int_{-\infty}^{\infty} \mathrm{pdf}_1\,(Z)\,\mathrm{DZ} \tag{7}$$

$$\mathrm{Er}_2\,(\mathrm{Th}) = \int_{T}^{\infty} \mathrm{p}_{\mathrm{df}2}\,(Z)\,\mathrm{DZ} \tag{8}$$

$$\mathrm{Er}\,(\mathrm{Th}) = \mathrm{P}_2\mathrm{Er}_1\,(\mathrm{Th}) + \mathrm{P}_1\mathrm{Er}_2\,(\mathrm{Th}) \tag{9}$$

where, Er(Th) is the total fault in cataloguing of the pixels as an object or the background. The error should be minimized in order to optimize the results. This can be achieved by taking the derivative of the following equation and setting it to nil:

$$\frac{\delta \mathrm{Er}\left(\mathrm{Th}\right)}{\delta \mathrm{Th}}=0 \tag{10}$$

Given a Gaussian_pixel_density, the value of Pval(Z) can be considered as follows:

$$\mathrm{Pval}\left(\mathrm{Z}\right)=\left(\frac{\mathrm{P}_1}{\sqrt{2\pi\sigma_1}}.\mathrm{e}^{-\frac{\left(\mathrm{z}-\mu_1\right)^2}{2\sigma_1^2}}\right)+\left(\frac{\mathrm{P}_2}{\sqrt{2\pi\sigma_2}}.\mathrm{e}^{-\frac{\left(\mathrm{z}-\mu_2\right)^2}{2\sigma_2^2}}\right) \tag{11}$$

where, $\sigma_1$, and $\sigma_2$ $\Rightarrow$ The density region's standard deviation, $\mu_1$ *and* $\mu_2$ $\Rightarrow$ Mean of intensity of pixels in regions, $\mathrm{P}_1$ and $\mathrm{P}_2$ $\Rightarrow$ Probability of background and object pixels a priori.

Subsequently, the updated assessment of "Th" can be determined by substituting it into the subsequent equation:

$$\mathrm{A\_T}^2+\mathrm{B\_T}+\mathrm{C}=0 \tag{12}$$

$$\mathrm{A}1=\sigma_1^2-\sigma_2^2 \tag{13}$$

$$\mathrm{B}1=2\left(\mu_1.\sigma_2^2-\mu_2.\sigma_1^2\right) \tag{14}$$

$$\mathrm{C}1=\sigma_1^2.\mu_2^2-\sigma_2^2.\mu_1^2+2\sigma_1^2.\sigma_2^2\ln\left(\frac{\sigma_2\mathrm{P}_1}{\sigma_1\mathrm{P}_2}\right) \tag{15}$$

Fig 4 indicates the proposed methodology of the research work:

When an image is clear, it becomes more straightforward and efficient to precisely segment the lesion region. We enhance image quality by utilizing image intensity values along with morphological operators and thresholding to eliminate artifacts such as hair and veils. To augment our training dataset and enhance model robustness, we applied various techniques including rotation, flipping, scaling, and color jittering. These augmentation strategies help mitigate overfitting and bolster model generalization. Our experiments showed that incorporating data augmentation significantly improved both accuracy and generalization of the model compared to evaluations conducted without these techniques.

**Image Resize.** We employed advanced image resizing methods that maintain critical features and incorporated multi-scale analysis. Additionally, we used convolutional neural networks (CNNs) tailored for high-resolution images to ensure robust feature extraction. Dermoscopy images offer a wide range of pixels that have a high resolution, and their computation is difficult to manage. High-pixel images are scaled up to 50% to decrease the amount of computation required.

***Step 3:*** Data reduction stores fewer images in a smaller amount from the original data. The whole collection comprises several shots with noise, artefacts, and some blurry images. These have obtained the best classification rate from the complete dataset. In certain situations, low-contrast images of injuries with infiltrators close to them display color illumination. Some photos with these qualities were manually deduced in the proposed R-CNN model. After deducting the photos, 6136 benign lesions and 979 malignant lesions are considered.

***Step 4:*** The Region Detection Function plays a crucial role in feature extraction, a key step in the proposed methodology. Region of Interest (ROI) detection is widely applied in various domains, including security surveillance, medical

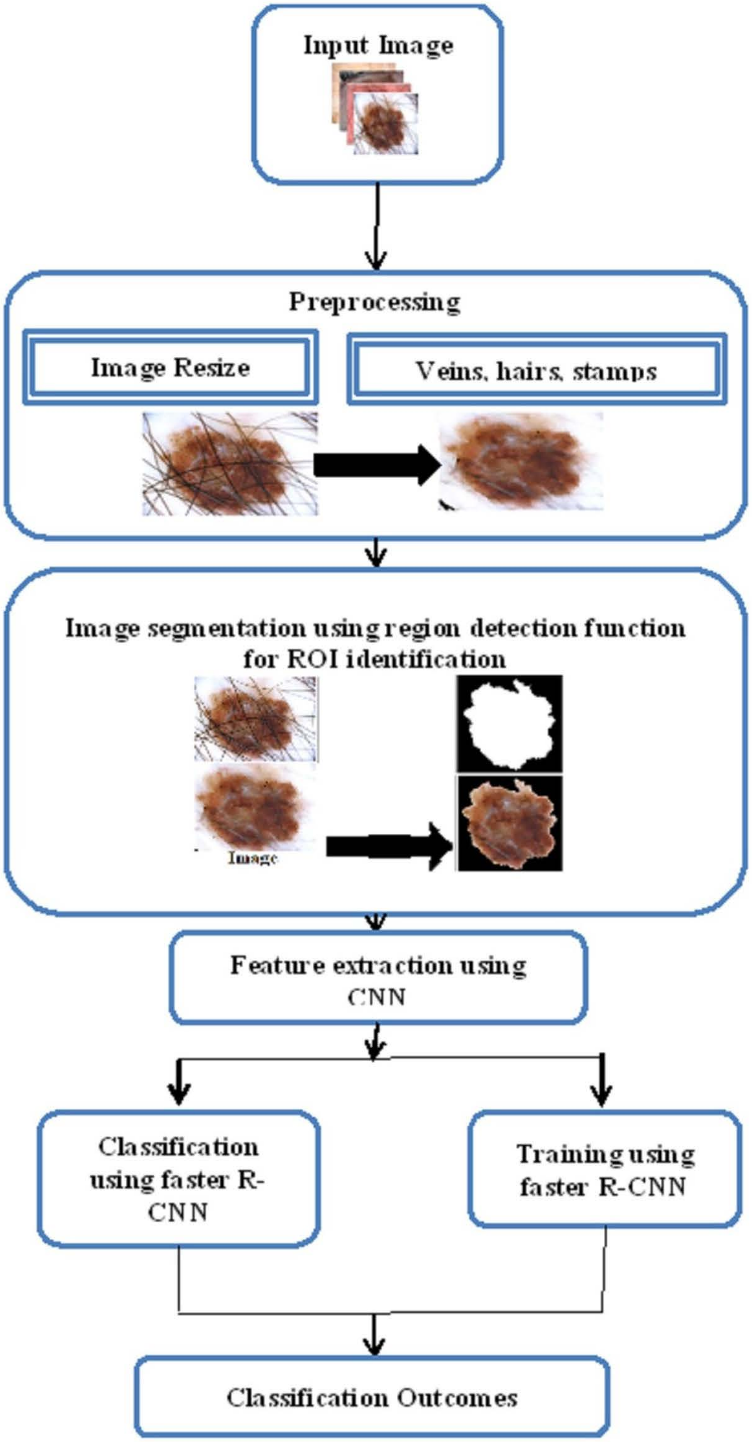


**Fig 4. Proposed methodology.**

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imaging, database management, and remote sensing. ROI categorization can be performed either manually or automatically. Significant research has focused on developing automated ROI identification through image segmentation techniques, with the best separation method depending on the specific requirements of the application. We propose a hybrid approach, FrCN-(U-Net), for image segmentation, which integrates features of both techniques to enhance segmentation accuracy.

***Step 5:*** To isolate the skin lesion from neighboring skin soft tissue and artifacts such as air bubbles, tresses, and to handle color space transformations, we employ mean thresholding and Region of Interest (ROI) extraction techniques.

Following this, the Region_of_Interest (ROI) image is processed in conjunction with a set of handcrafted features, which are derived based on shape and color attributes. This analysis utilizes binary segmentation to enhance the precision of feature extraction. The Asymmetry Borders-Colors-Dermatoscopic Structures (ABCD) approach employs that are based on the color and form aspects. To extract deep learning features, ImageNet classification task-trained CNN architecture is selected and utilized as the feature separator as illustrated in the image. The Mutual Information (MI) criterion is used to concatenate the features into a single vector to fuse them.

The selected features are interpretation of a medical characteristics using the image processing. Sirakov et al. [53] established a strategy for estimating a lesion's asymmetry. The symmetry mask S_(I_bin) is then generated by rotating it through 180 degrees, and synthetic picture "A" is determined as follows:

$$A = I_{bin} \cup S_{I_{bin}} \tag{16}$$

where "A" is a produced picture that comprises the lesion's non-overlapping portions, referred to as false symmetry "F_S", so applying

$$Symm_{0^\circ} = 1 - (F\_S/A) \tag{17}$$

The preceding method is refined by rotating the generated image "A" around both the major and minor axes using the same technique. To end with, the average symmetry value among these two battle-axes is computed using the following equation:

$$Symmetry = \frac{Sym_{0^\circ} + Sym_{90^\circ}}{2} \tag{18}$$

The symmetry values are scaled within the range [0,1], where a lesion is considered increasingly symmetrical as the index approaches the upper bound of "1". The in-depth details of the different selected features is shown below.

Shape Features: Geometric or shape features [54] can be used to express human perception by numerically describing an object or a form.

For the shape features, the below equation is used:

$$Area = \sum_{x=1}^{m1} \sum_{y=1}^{n1} I_{bin}(x1, y1) \tag{19}$$

where "m1" and "n1" specify the dimensions of the image, and "x1" and "y1" indicate the pixel coordinates; consequently, the area under consideration corresponds to the number of pixels contained within the ROI.

$$Perimeter\_P = \sum_{i=1}^{m1} \sqrt[2]{(x_1 - x_{i-1}) + (y_1 - y_{i-1})} \tag{20}$$

Here, (x,y) denotes the coordinates of the i-th pixel that outlines the boundary of the region. The perimeter is determined by aggregating the total count of pixels that delineate the edge surrounding the Region of Interest (ROI) of the lesion, thereby capturing the detailed contour of the lesion.

$$\text{Circularity\_C} = \frac{4\pi.\,\text{Area}}{\text{Perimeter}^2} \tag{21}$$

In this context, the diameter is computed by evaluating the lengths of the minor and major axes of the nature, as inferred from the second central instant. This metric quantifies the extent of the shape by measuring the distance between two sets of arguments on its perimeter, thereby capturing the shape's dimensions along its principal axes.

$$\text{Eccentricity\_E} = \frac{\left(\mu_{0,2} - \mu_{2,0}\right)^2 + 4\mu_{1,1}}{\text{A}} \tag{22}$$

which quantifies the aspect ratio of a main axis's length to the minor axis's length.

Colour Features: In precise the A.B.C.D. rule, is used as the usual of a colors confined, features on the Pigmented Skin Lesion (PSL). As a result, these qualities are replaced with statistical properties derived from colour spaces. The following characteristics are utilised in this study:

$$\text{Min}_{\text{channel}} = \min\left[\text{I}_{\text{channel}}\left(\text{x}, \text{y}\right)\right] \tag{23}$$

$$\text{Max}_{\text{channel}} = \max\left[\text{I}_{\text{channel}}\left(\text{x}, \text{y}\right)\right] \tag{24}$$

$$\text{Var}_{\text{channel}} = \text{var}\left[\text{I}_{\text{channel}}\left(\text{x}, \text{y}\right)\right] \tag{25}$$

$$\text{Mean}_{\text{channel}} = \overline{\left[\text{I}_{\text{channel}}\left(\text{x}, \text{y}\right)\right]} \tag{26}$$

where, $\text{I}_{\text{channel}}\left(\text{x}, \text{y}\right)$ refers to the image data from the selected channel of a skin lesion image in the RGB color space.

***Step 6:*** This step contains two parts which are given below:

- *Classification using R-CNN:* Image classification requires extracting features from a picture to identify patterns in a dataset. In terms of processing, using a CNN for image classification would be exceedingly expensive.
- *Training using R-CNN:* In this, training is done on data using R-CNN.

***Step 7:*** After training, the model's enactment is measured by means of various parameters and compared to the results from leading-edge architectures.

## V. Implementation results and discussion

This segment outlines the enactment process and provides an analysis of the results from the suggested methodology, benchmarking its effectiveness against established methods.

### A. Preprocessing and segmentation results

The preprocessing steps include image resizing, removal of irrelevant items such as veils or hairs, and conversion to grayscale images for more efficient feature extraction. Benign and melanoma preprocessing results are expressed in Figs 5 and 6. A cleaner input for the following segmentation is thereby ensured.

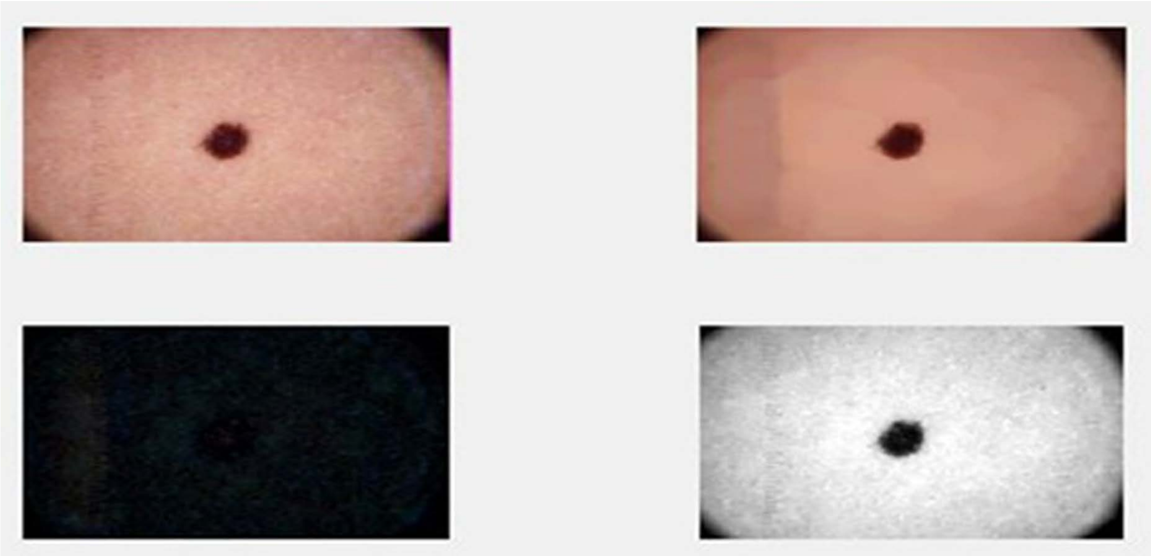

**Fig 5. Contour array image of Benign.**

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Thereafter was the hybrid segmentation approach that combines the features of FrCN and U-Net architecture for segmenting regions of interest within the images. The method proposed corroborated improvement in segmentation accuracy when compared with individual techniques. The performance results for the segmentation process are shown in Table 2, which shows the sensitivity, specificity, and accuracy for benign, melanoma, and overall cases. The hybrid approach exceeded both FrCN and Unet numbering among its cohort with an overall accuracy of 95.8%.

### B. ROC curve analysis

So as to establish what is the reliability of the segmentation method, ROC curves for benign, melanoma, and overall cases were generated. The ROC curve for benign cases is given in Fig 7, showing that the proposed FrCN-(U-Net) method outperformed the other techniques from start to finish. The ROC curve for melanoma cases is shown in Fig 8, whereby it had emerged that the proposed method constantly outperformed FrCN and U-Net. The ROC curve for overall cases in Fig 9 can summarize the efficacy of the hybrid approach in all categories.

The ROC curve of the suggested FrCN-(U-NeT) in comparison by means of the FrCN and U-NeT method of the Benign cases is depicted in Fig 7. According to this curve, the suggested approach of segmentation for benign circumstances outpaces the prior techniques.

Fig 9 illustrates the ROC curve for the proposed FrCN-(U-Net) approach in comparison with the FrCN and U-Net methods for melanoma cases. The curve indicates that the proposed FrCN-(U-Net) segmentation method significantly outperforms the existing techniques for melanoma detection.

The ROC curve of the suggested FrCN-(U-Net) in comparison with FrCN and U-Net methods of the Overall cases is depicted in Fig 10. The curve reveals that the proposed segmentation method significantly outperforms previous techniques across all cases.

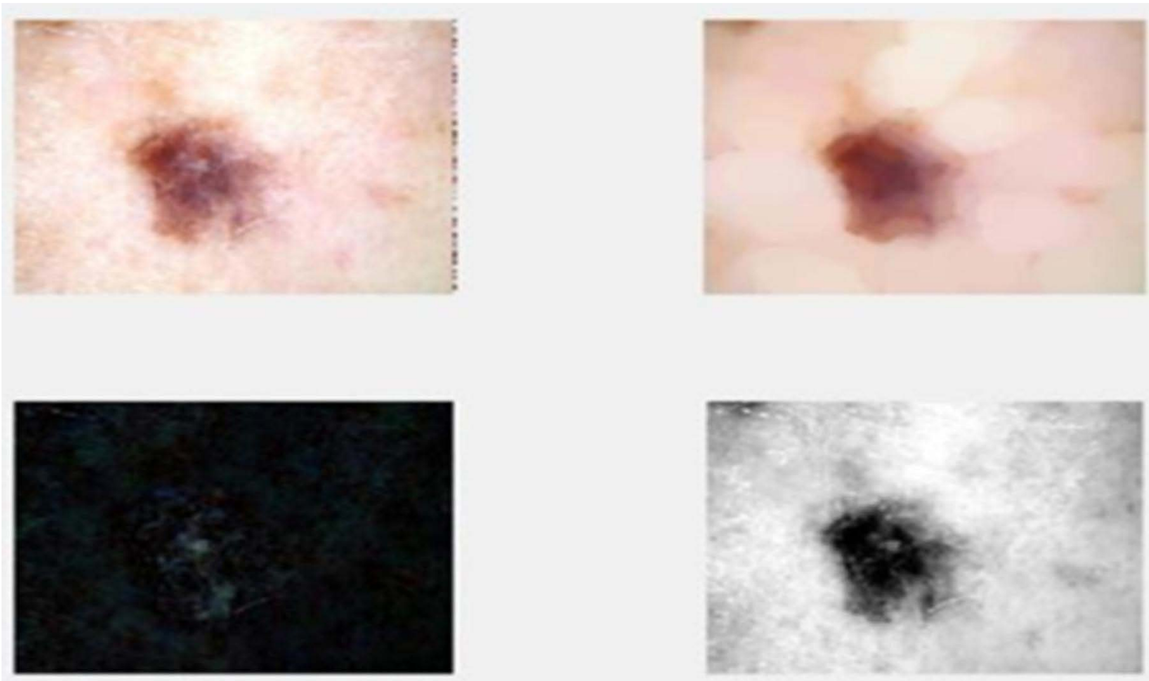

**Fig 6. Contour array image of Melanoma.**

https://doi.org/10.1371/journal.pone.0322659.g006

**Table 2. Evaluation of FrCN-(U-Net) Segmentation Performance Relative to FrCN and U-Net.**

| Technique | Benign | | | Melanoma | | | Overall | | |
|---|---|---|---|---|---|---|---|---|---|
| | Sensitivity | Specificity | Accuracy | Sensitivity | Specificity | Accuracy | Sensitivity | Specificity | Accuracy |
| **U-Net [38]** | 76.76 | 97.26 | 92.89 | 58.71 | 96.81 | 84.98 | 67.15 | 97.24 | 90.14 |
| **FrCN [38]** | 88.95 | 97.44 | 95.62 | 78.91 | 96.04 | 90.78 | 85.40 | 96.69 | 94.03 |
| **Proposed** | 89.8 | 98.9 | 96.21 | 79.8 | 97.12 | 92.23 | 86.8 | 97.5 | 95.8 |

https://doi.org/10.1371/journal.pone.0322659.t002

## C. Classification results

Fig 10 delivers a thorough evaluation of the model's performance metrics, demonstrating its adeptness at classifying images into benign and melanoma categories with notable precision—achieving an accuracy of 94.44%, specificity of 91.07%, sensitivity of 96.22%, and an F-score of 95.77. Table 3 further complements this analysis by offering an elaborate comparative review of the proposed model against established methodologies, clearly illustrating that the proposed approach significantly surpasses prior algorithms in classification efficacy and overall performance.

Although the hybrid segmentation strategy we have developed, which combines FrCN and U-Net, exhibits encouraging outcomes, it is not without its limits. Generalizability may be impacted by the dataset's potential exclusion of some real-world variables. Real-time application is limited by the large processing needs, indicating a need for model optimization. The efficacy of the model is now restricted to the differentiation of benign from melanoma lesions, suggesting the necessity of broadening its application to encompass more skin disorders. Reliance on high-quality photos might also affect how well noisy or lower-quality photographs function.

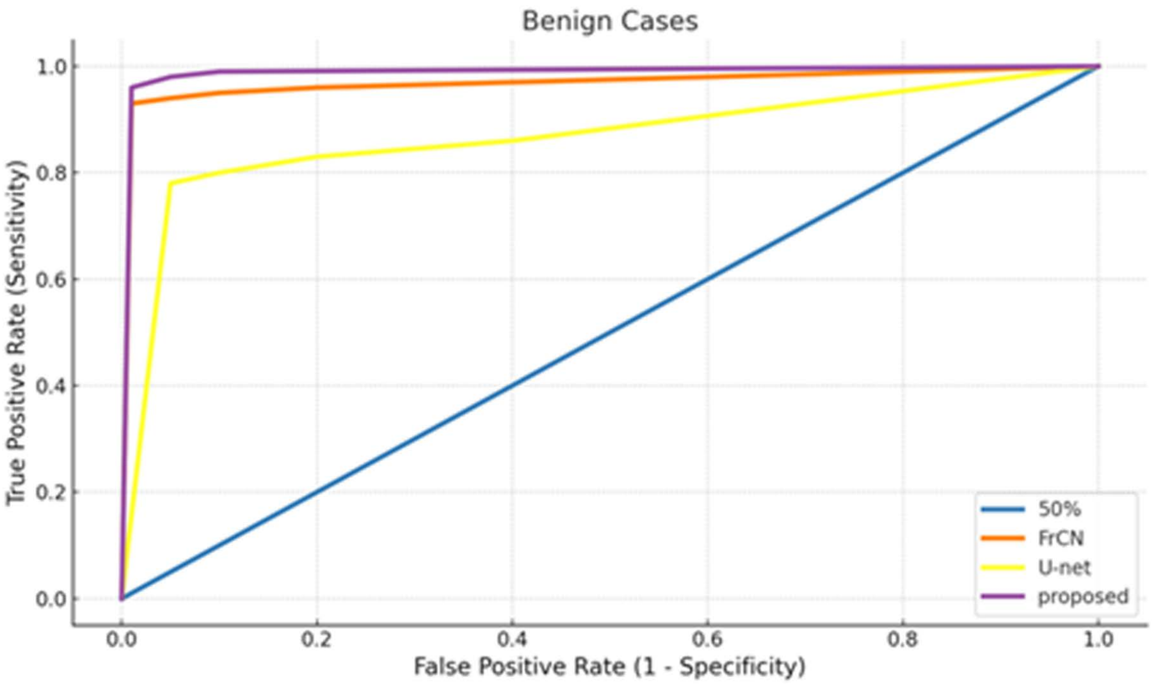


**Fig 7. ROC curves for the Benign cases.**

https://doi.org/10.1371/journal.pone.0322659.g007

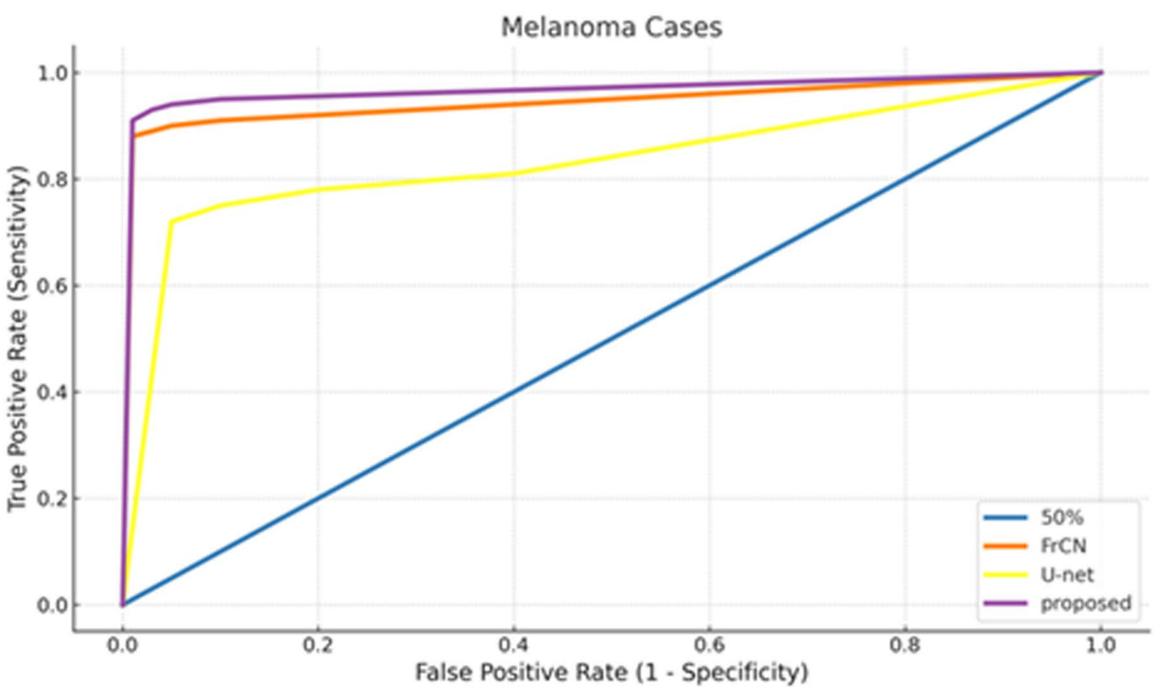


**Fig 8. ROC curves for the Melanoma case.**

https://doi.org/10.1371/journal.pone.0322659.g008

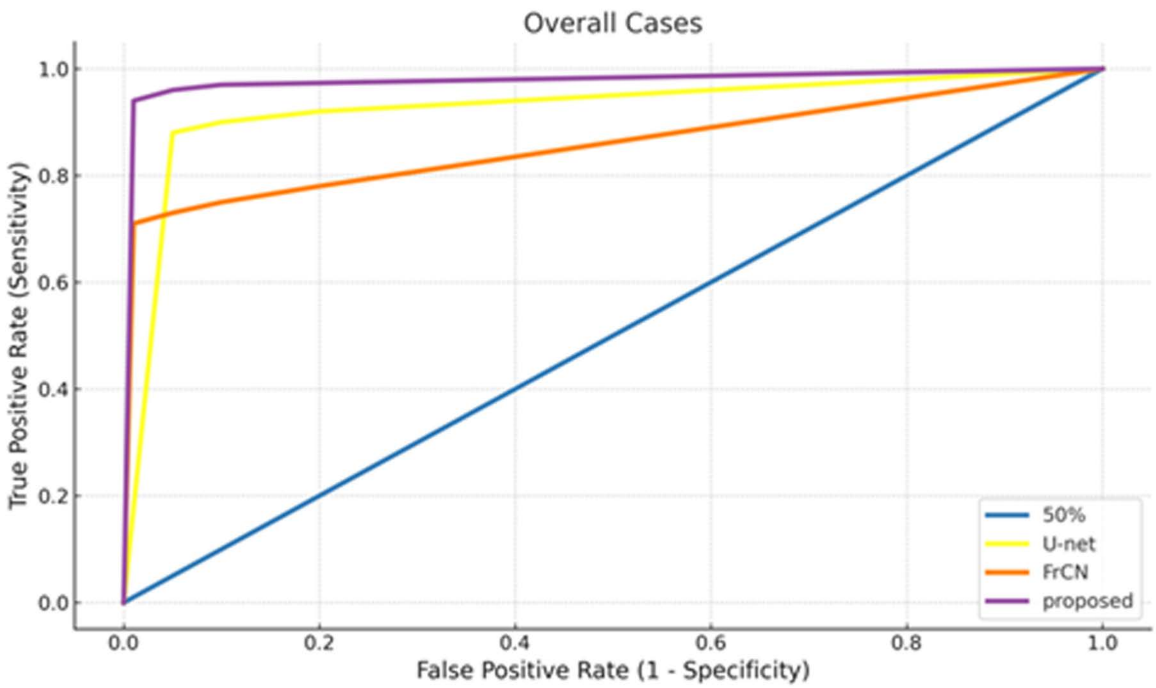


**Fig 9. ROC curves for the overall cases.**

https://doi.org/10.1371/journal.pone.0322659.g009

```
[[102   5]
 [  4  51]]
Accuracy is 94.44444444444444
Specificity is 91.07142857142857
Sensitivity is 96.22641509433963
Fscore is 95.77464788732395
```

**Fig 10. Model performance metrics: Accuracy, specificity, sensitivity, and F-Score.**

https://doi.org/10.1371/journal.pone.0322659.g010

**Table 3. Performance comparison of R-CNN and leading techniques.**

| Parameter | Li et al. [55] | Adjed et al. [56] | Almaraz et al. [21] | Proposed |
|---|---|---|---|---|
| **Accuracy** | 85.55% | 86.07% | 92.40% | 94.44% |
| **Specificity** | 86 | 78.93 | 90 | 91.07 |
| **Sensitivity** | – | 93.25 | 86.41 | 96.22 |
| **F-Score** | 86 | – | 89.16 | 95.77 |

https://doi.org/10.1371/journal.pone.0322659.t003

## VI. Conclusion

Skin malignancy residues one of the most prevalent and hazardous forms of malignancy. There is an immediate need for a model that can automatically classify the generous of skin malignancy, such as melanoma and benign, by extracting the most discriminative information in an effective manner. Numerous methods have been used by researchers to identify traits that are distinctive in the identification of skin malignancy. Skin malignancy remains one of the most prevalent and insidious forms of cancer globally, with a sharply rising incidence attributed to a multitude of influencing factors. The imperative for early detection is underscored by its critical importance in facilitating timely diagnosis and optimizing therapeutic interventions, thus playing a pivotal role in effective disease management. The R-CNN model has shown superior performance over other methodologies discussed in this study, achieving a notable accuracy of 94.44%. Moreover, the study underscores the essential role of segmentation in the diagnostic process. The proposed hybrid FrCN-(U-Net) methodology significantly advances segmentation accuracy, outperforming contemporary approaches with a significant accuracy of 95.8% across all evaluated cases. Every execution is carried out using the ISIC 2017 and 2018 dataset. In order to achieve a model accuracy of about 100%, subsequent work on the huge dataset containing a few additional labelled skin lesions will be necessary to build a successful deep learning model, including the necessary pre-processing processes.

## VII. Limitations and future work

While the ISIC datasets have provided a great and decent basis for training and evaluating the proposed model, real-life variations, such as images captured under various lighting conditions, angles, and lower resolution, do not seem to have been fully captured in them. These affect the generalizability of the model and its suitability for actual applications. Future work, therefore, will be focused on the incorporation of additional datasets comprising the variabilities elaborated and the implementation of advanced data augmentation techniques in simulating these conditions. In addition to such efforts, exploring the possibility of domain adaptation methods can further help achieve the robustness of the model therefore validating it under various imaging conditions.

The study presents a model training for skin cancer detection, but focuses on clinical usability. Next steps include integrating the model with EHR systems for clinical settings and developing an end-user interface for dermatologists. These improvements will strengthen the model's clinical applicability and facilitate its integration into routine dermatological practice.

## Author contributions

**Conceptualization:** Puneet Thapar, Manik Rakhra.

**Formal analysis:** Arfat Ahmad Khan.

**Investigation:** Seifedine Kadry.

**Methodology:** Deepak Prashar, Leo Mrsic.

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