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Enhancing Melanoma Skin Cancer Detection and Classification: U-Net Segmentation and Feature Fusion of Deep Learning Algorithms

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Abstract- Human skin cancer is the most prevalent type of cancer and poses a significant threat to life, particularly, melanoma skin cancer, which exhibits a high mortality rate. Accurate detection and classification of melanoma skin cancer continue to be essential for timely treatment and improving patient diagnosis. Traditionally, painful, invasive and time-consuming biopsies are used to detect melanoma skin cancer. However, recently, computer-aided diagnosis of melanoma has become crucial. Thus, in this study, the researcher proposes a novel approach combining the feature extraction capability of the VGG16 and ResNet-50 deep learning algorithms with the precise segmentation power of the U-Net architecture. By combining these methodologies, the study aimed to achieve enhanced accuracy in distinguishing melanoma skin cancer as benign or malignant. The proposed method leverages the U-net segmentation algorithm to accurately delineate lesion boundaries and highlight crucial diagnostic areas, and the VGG16 and ResNet-50 models to extract high-level features from melanoma images, capturing textures and intricate patterns indicative of melanoma skin cancer. With a precise segmentation algorithm and the fusion of rich features from deep learning models enable a comprehensive analysis of melanoma characteristics, facilitating more reliable classification. The study used a total of 10606 images of melanoma skin cancer, and the experimental result demonstrates promising results, achieving a classification accuracy of 93% in distinguishing benign and malignant cases. As the experimental result shows, it validates the effectiveness of the proposed method in accurate classification of melanoma skin cancer. This study contributes to advancing melanoma detection capability and paving the way for more accurate dermatological diagnostic tools.

Keywords- Melanoma, Skin cancer, U-net Segmentation, VGG16, ResNet-50, Feature fusion, Classification

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I. Introduction

The skin serves vital functions in maintaining body temperature and shielding us from environmental hazards like sunlight. Unfortunately, numerous skin ailments, including malignant tumors driven by genetic factors, can emerge. Among these, squamous cell carcinoma, melanoma, and basal cell carcinoma stand out, posing significant risks with low survival rates. Collectively, these malignancies yield over 3.5 million diagnoses annually, with melanoma being particularly menacing [1], [2]. Melanoma, among the most perilous cancers, stems from immune alterations in melanocytes scattered in skin layers, hair, eyes, and other tissues, culminating in malignant growths [2]. Typically manifesting as black or brown lesions, melanomas may also present in red, pink, or purple hues. Studies from a British university underscore that 86% of melanomas result from ultraviolet (UV) radiation exposure, with the risk doubling after just five sunburns. Melanoma often progresses to skin cancer, notably in individuals with fair complexions. Nonetheless, detecting melanoma early, prior to symptom onset, offers a promising 90% cure rate. Currently, many studies [1], [2], [3], [4] have been conducted to detect and classify melanoma skin cancer using deep learning algorithms. However, segmentation of cancerous regions is important to classify and detect melanoma cancer [5], [6]. Moreover, segmenting medical images presents a challenging endeavor due to a multitude of constraints imposed by the medical image acquisition process, the nature of the pathology, and diverse biological variations. The researcher [5] states that the U-Net model demonstrates the capability to efficiently segment images even when trained on a limited number of labeled training images. New findings [6] demonstrate the critical significance of network depth, with top-performing outcomes on the demanding ImageNet dataset leveraging "very deep" models, ranging from sixteen to thirty layers. Various networks gather features through distinct means, leading to attention on diverse regions; integrating multiple deep CNN networks enriches features. Thus, the study proposes a fusion of ResNet-50 and VGG16 for melanoma skin cancer detection and classification. The primary contributions of this study are outlined as follows:

- The study developed a novel deep CNN architecture that fuses Feature from the ResNet-50 and VGG16 architectures
- Data augmentation techniques were employed to enhance the training dataset
- A novel U-Net architecture was implemented for segmentation
- The researcher evaluated the proposed model, which showing promising results

II. Related Work

Various attempts have been made to detect and classify melanoma skin cancer [7, 8, 9, 10, 11, 12, 13, 14, 15]. The non-invasive medical image processing plays a significant role in diagnosing different diseases in clinical diagnosis. Hiam et al. introduce an image processing technique that provides an automatic image analysis tool for an accurate evaluation of the disease. The steps in these techniques involve image data collection, preprocessing, segmentation by thresholding, feature extraction by gray level co-occurrence matrix, asymmetry border, color diameter, feature selection using principal component analysis, and

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classification using support vector machines, and they achieved 92.1% accuracy [7]. Melanoma is the most dangerous and worst type of skin cancer that can extend into deeper layers of the skin. However, if diagnosed at an early stage, its survival rate is 96%. Using expert dermatologists, equipment, and biopsies to diagnose melanoma is an expensive approach. To avoid the expensive diagnosis, Arslan et al. proposed an image processing and machine learning method to classify and segment skin lesions as benign and malignant. The OTSU thresholding segmentation algorithm, grey level co-occurrence matrix features for texture identification, histogram-oriented gradients for object and color identification, principal component analysis for dimensionality reduction, synthetic oversampling technique for class imbalance problem, and SVM and RF algorithms were used for classification. The method achieved 93.89% of classification accuracy [8].

Melanoma is one of the most prevalent forms of skin cancer, and early identification of melanoma cancer is essential for treatment of melanoma before spreading to other body parts. Using deep learning techniques can accurately detect melanoma with subtle differences. Kavitha et al. employed an image preprocessing technique for removing artifacts in the row dataset and a convolutional neural network (CNN) for classification and detection and achieved an accuracy of 84.32% [9]. Different convolutional neural network architectures and machine learning classifiers are used to detect melanoma skin cancer. Kakularam Viksas and Rama Parvathy employed a convolutional neural network and decision tree algorithms to detect melanoma skin cancer and achieved an accuracy of 75.58% with CNN and 85.61% of accuracy with decision tree [10].

An image processing technique to detect and classify melanoma skin cancer is essential to overcome detecting melanoma skin cancer using traditional methods through painful and time-consuming biopsies. Chandran et al. introduce two methods for detecting melanoma skin cancer as benign and malignant. The first method employs AlexNet, LeNet, and VGG16 deep learning algorithms, and the highest accuracy obtained is 91%. While in the second method they employed a support vector machine with a default RBF kernel and achieved 86.6% of classification accuracy [1]. When melanoma skin cancer is detected and treated early, it has a 98% 5-year survival rate, and due to late-stage diagnosis, over 10,000 people are lost each year. Simon Kalouche proposed a fast and expensive computer vision based machine learning tool to classify suspicious skin lesions as benign and malignant. The logistic regression, fine-tuned, pre-trained VGG16 CNN, and deep neural network models were used and achieved 78% of accuracy [11].

Currently, employing a machine-learning-based classification and detection approach is the most dominant and robust approach to detecting skin cancer. Atheer et al. introduce an automatic malignant and benign skin cancer classification using a hybrid deep learning approach. Resnet-50, Xception, and VGG16 models are used for feature extraction and stacking of SVM, RE, NN, KNN, and logistic regression methods are used as classifiers. The maximum 90.9% of classification accuracy is achieved in Xception with stacking classifiers [12]. Deep learning algorithms have been determined as efficacious for the categorization of skin cancer, and they are helpful for early identification and treatment. Naga et al. proposed a

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CNN based approach for classifying skin cancer as benign and malignant and achieved 92% of training accuracy [13].

Due to their effectiveness and efficiency, recently, computer-aided diagnostic systems have gained more popularity than the time-consuming traditional methods of skin cancer detection. Muhammad et al. proposed an explainable deep learning-based approach for classifying skin cancer into benign and malignant. The pre-trained DenseNet201 and MobileNetV2 deep learning models are used by modifying at the end of the model by stacking three convolutional layers and achieved 95.5% accuracy [14]. For appropriate treatment and increasing the survival rate of patients, physicians use computer-developed diagnosis systems to diagnose skin cancer. Thus, Taher et al. introduced an automated system for the classification of benign and malignant benign skin cancers. The pre-trained AlexNet model is employed by modifying the softmax layer according to binary classification and detection and achieved 87.1% of accuracy [15]. However, all the proposed methods aren't sufficient for detecting melanoma skin cancer. In addition, there is a necessity for a generalized and enhanced deep CNN algorithm model for the classification of melanoma skin cancer.

III Methodology

The proposed methodology encompasses image acquisition, image preprocessing, image segmentation, feature extraction, feature fusion, and classification. The following figure (**see Figure 1**) depicts the architecture of the proposed system called enhancing melanoma skin cancer detection and classification (EMCDC).

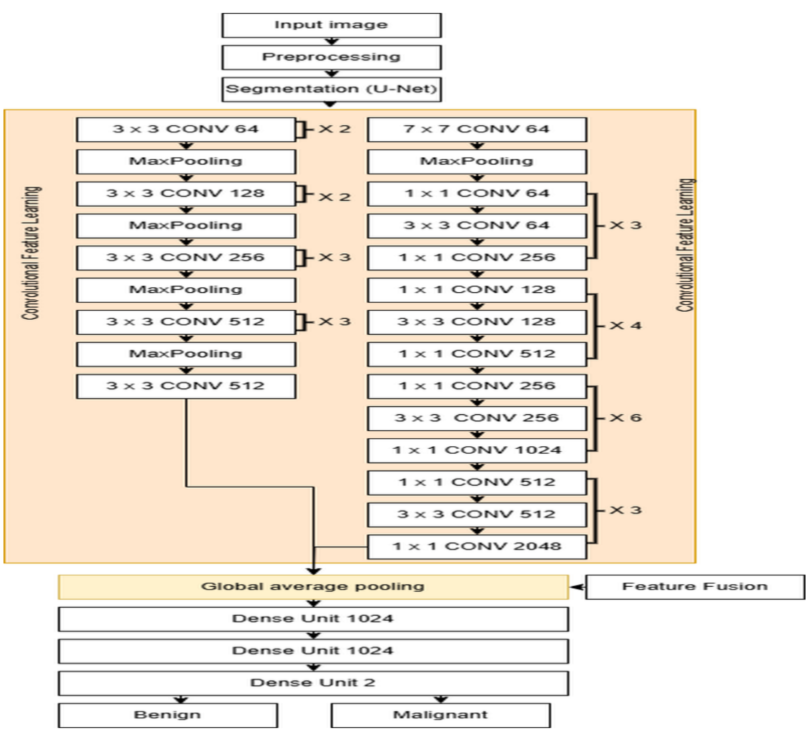

Figure 1: Architecture of the Proposed Model

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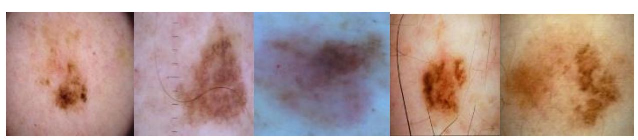
A. Input Image

A total of 10,606 images of melanoma skin cancer were collected from Kaggle, a publicly available repositoryvia the following link:

https://www.kaggle.com/datasets/hasnainjaved/melanoma-skin-cancer-dataset-of-10000-images. The researchertook images of benign, malignant melanoma skin cancer, and all were saved with .JPEG filename extension and resized into 256 x 256 pixel resolution. The overall description of the dataset is given by the following figure (**see Figure 2**).

Figure 2: Quantity of the Dataset

(a)



(b)

Figure 3: (a) Sample Images of Benign and (b) Sample Images of Malignant

B. Image Preprocessing

Deep learning algorithms require image preprocessing for accuracy and feature detection [16]. Hence, in this step, the researcher refined image data for deep learning, enhancing image quality by removing noise and artifacts for improved classification accuracy. The study involved grayscale conversion, noise filtering, and contrast adjustment. Binarization reduces unwanted information in grey-scaled images, enhancing algorithm performance and feature extraction.

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C. Segmentation

Medical image segmentation is a difficult step due to procurement procedures, pathology diversity, and biological variations, limiting expert analysis due to a scarcity of specialists. But, this step is crucial as it minimizes external noise surrounding the lesion [5],[16]. Recently, recent advancements in deep learning networks have yielded enhanced segmentation models, exhibiting high accuracy across diverse datasets. Especially the encoder-decoder model that utilizes a two-stage process to map data points from the input to the output domain. The encoder compresses the input data (x) into a latent space representation, while the decoder generates the output based on this representation[5]. According to [5], [17], [18], [19] The U-Net model efficiently segments images with minimal labeled training data by leveraging location information from the down sampling path to generate accurate segmentation maps. Therefore, the researcher utilized the U-Net model as a segmentation model in this study. The preprocessed images undergo feeding into the U-Net model for segmentation of the desired region. The U-Net segmentation architecture comprises elements for both up-sampling and down-sampling. The architecture employed for this study is illustrated in the following figure (**see Figure 4**).

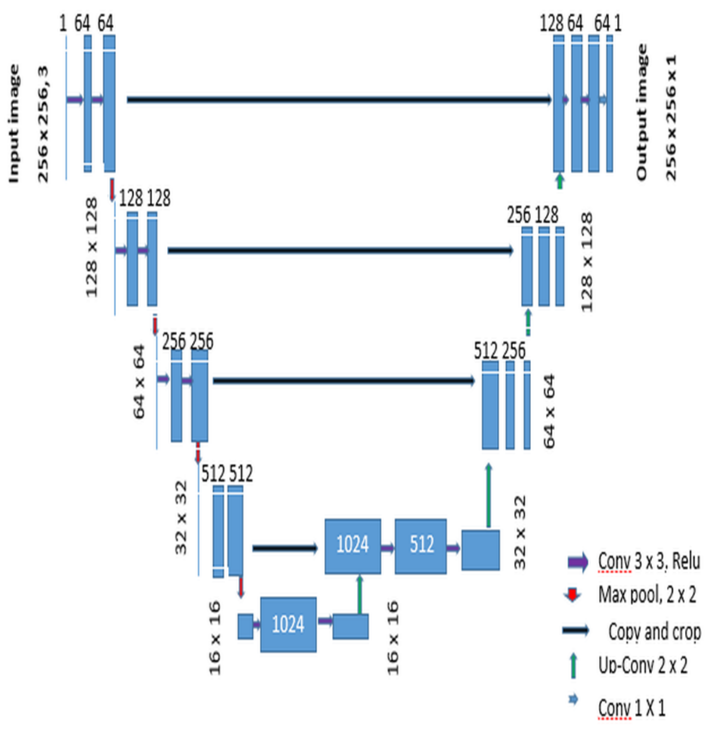

Figure 4: Proposed U-Net Architecture for Segmentation

As shown in Figure 4, to segment the input image, the image must go through the down and up sampling. On the down sampling, 256 x 256 input sizes of color images were fed to a series of convolutional layers. A size of 64, 128, 256, and 512 filter sizes were used in the

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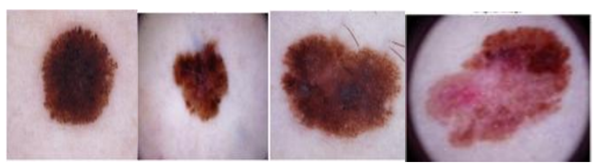
down sampling. After each double 3 x 3 convolutional layer that was used for extracting and mapping the features of these input images, the images were compressed by double through 2 x 2 Max pooling. After the convolutional layer, the Rectified Linear Unit Layer (ReLu) activation layer is applied. On the up sampling, a size of 1024, 512, 256, 128, 64, and 1 filter sizes were used to expand the input image. After the double convolutional layer, the image is doubled and concatenated with the corresponding layer on the down sampling side. This is important because if the model can't learn in the up sampling layer, the model uses the old information obtained in the down sampling to continue its model training [20]. At the bottleneck, the convolution layer contains a filter size of 1024, and the image dimension becomes 16 x 16. The following figure (**see figure 5**) depicts the segmented image using the above U-Net architecture.



(a)

(b)

Figure 5*:* (A) Original Images and (b) Respective Segmented Image of the **Original Images**

D. Convolutional Feature Learning for the Proposed Model

In the convolutional layer, the proposed model obtains relevant features from two different deep learning algorithms called VGG16 and ResNet-50. In this step, the features extracted from images using the VGG16 and ResNet-50 deep learning algorithms are combined into one feature that is more discriminating than the input features. In the use of deep learning algorithms for extracting image features, low-level features of the image are captured by the early layer of the network but have a higher resolution that contains more detailed information and is more positional. While, high level features are captured by the deeper layer but have stronger semantic information and have lower resolution and less ability to perceive details. Hence, the fusion of multi-scale features, model them together by utilizing different levels of features [21]. In the VGG16 architecture, 13 different 3 x 3 convolutional layers (Conv 3 x 3, 64 (2x), Conv 3 x3, 128 (2x), Conv 3 x3, 256 (3x), Conv 3 x3, 512 (3x), and Conv 3 x3, 512 (3x)) were used to extract relevant features. After each convolution, the researcher used a

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stride of 2 x 2 to reduce the size vertically and horizontally by half. In the ResNet-50 architecture, 5 different blocks are used to extract relevant features. Block one contains Conv 7 x 7, 64, block two contains ((Conv 1 x 1, 64, Conv 3 x 3, 64, and Conv 1 x 1, 64) x 2), block three contains ((Conv 1 x 1, 128, Conv 3 x 3, 128, and Conv 1 x 1, 256) x 4), block four contains ((Conv 1 x 1, 256, Conv 3 x 3, 256, and Conv 1 x 1, 1024) x 6), and block five contains ((Conv 1 x 1, 512, Conv 3 x 3, 512, and Conv 1 x 1, 2048) x 2). After convolutional feature learning, the features extracted from VGG16 and ResNet-50 deep learning algorithms are merged together through global average pooling. Then, the merged features are fed to a series of fully connected layers. In the fully connected layer, three fully connected layers were used: layer one and two contain 1024 neurons, and layer three contains 2 neurons with a softmax classifier.

IV Experiment

In this study, the researcher extracted features from VGG16 and ResNet-50 deep learning architectures, and all the features are merged using global average pooling. These extracted features are used to develop the model that can detect and classify melanoma skin cancer.

A. Experimental Setup

The researcher implemented the proposed model using Python programming language on a single 12 GB NVIDIA Tesla k80 Graphics processing unit, GPU provided by Google Colabs [22] , [23]. Out of 10,606 images, 70% of the images were allocated for training, and the remaining 20% were allocated for the validation/testing split. This resulted in 7423 images for the training split and 3183 images for the validation/testing split. For training, a batch size of 32 was used because the study used a limited single tesla k80 GPU [22]. The model is trained for epoch 100, an initial learning rate (lr=0.001), a batch size of 32, and with Adam optimizer.

B. Evaluation Metrics

To evaluate the proposed model, the researcher used standard performance measure metrics such as precision, recall, F1-score, accuracy, and confusion matrix. Based on studies of [22], [24], and [25] the mathematical formula and the description of precision, recall, f1-score, and accuracy are given below.

Recall measures the ability of a classification model to correctly identify all relevant instances of a particular class within a dataset. Mathematically recall is given in Equation (1).

$$\text{Recall} = \frac{\textit{True positives}}{\textit{True Positives} + \textit{False Negatives}} \tag{1}$$

Precision measures the accuracy of the positive predictions made by a classification model. Precision is calculated as the ratio of the number of true positive predictions to the sum of true positive and false positive predictions. Mathematically given precision is given in Equation (2).

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$$Precision = \frac{Truepositives}{TruePositives+FalsePositives} \quad (2)$$

The F1-score can be interpreted as a weighted harmonic mean of the precision and recall and is given in Equation (3).

$$F1 - score = \frac{2*(precision*recall)}{precision+recall} \quad (3)$$

Accuracy is the amount of correct predictions made compared to the total number of predictions made. Mathematically given in Equation (4)

$$Accuracy = \frac{Truepositives+TrueNegatives}{TruePositives+FalsePositives+FalseNegatives+TrueNegatives} \quad (4)$$

In addition, the confusion matrix is implemented to assess the proposed model performance. The confusion matrix provides a comprehensive representation of the correctly classified TP values, FP values that are categorized in the wrong class, false negative (FN) values that belong to the incorrect class, and correctly classified TN values in the other class [22]. Hence, the study used a confusion matrix as a performance measure, which is used to describe the performance of a classification model on the set of test data for which the true values are unknown.

C. Experimental Result

In this step, the study made different experiments to improve the performance of EMCDC by applying different techniques. In experiment one, the defined architecture is trained for epoch 100 by partitioning the entire dataset into 70% of training and 30% of validation/testing split. Additionally, the study didn't apply any data segmentation to the training or validation/testing data and the detail of the obtained result is given below.

Table 1. Training Detail of EMCDC before Applying U-Net Segmentation

Model	Optimizer	Epochs	Learning Rate	Training Accuracy
EMCDC	Adam	100	0.001	90.62%

Validation Accuracy	Training Loss	Validation Loss	Number of correctly classified	Number of misclassified
90.13%	22.33%	24.04%	2851	332

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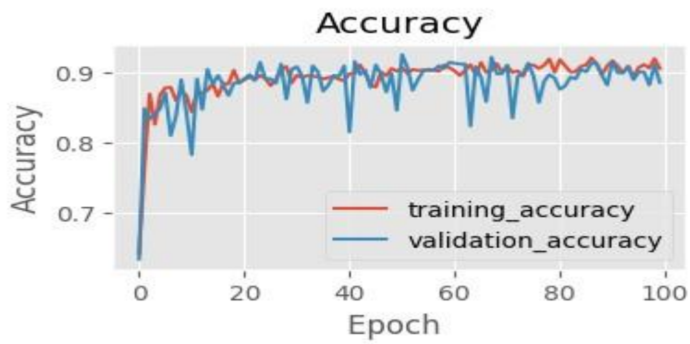
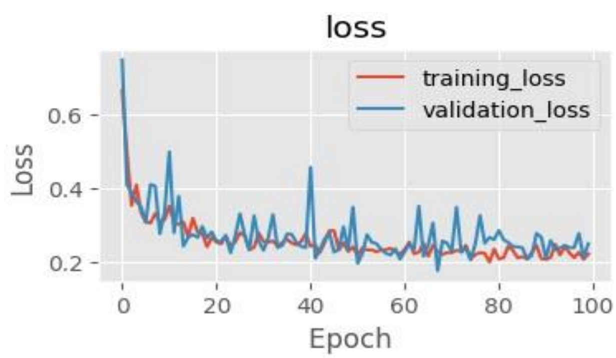


(a)



(b)

Figure 6: (a) Training and Validation Accuracy the Proposed Model, (B) Training and Validation Loss of the Proposed Model before Applying U-Net Segmentation

Table 2. Performance measure of the Proposed Modelbefore applying U-net Segmentation

Classes	Precision	Recall	F1-score	Support
Benign	0.85	0.97	0.91	1651
Malignant	0.97	0.81	0.88	1532
Accuracy			0.90	3183
Macro avg	0.91	0.89	0.90	3183

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Weighted avg	0.91	0.89	0.90	3183

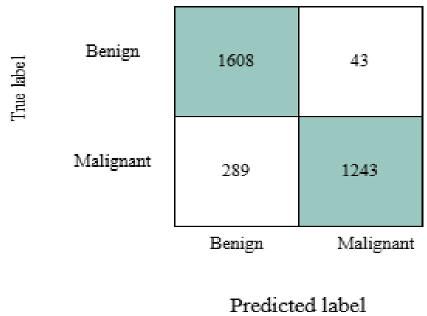
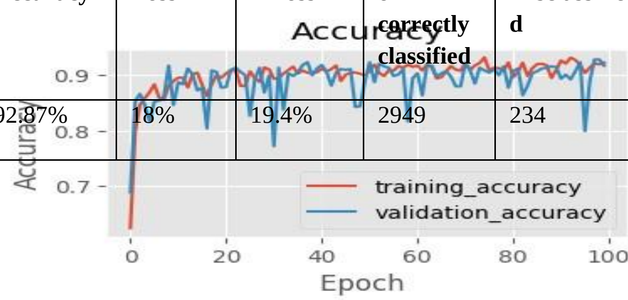


Figure 7: Confusion Matrix of the Proposed Model before Applying U-Net Segmentation

As shown in the above tables (**see table 1 and table 2**) and figures (**see figure 6 and figure 7**), the performance of the proposed model is not enough to detect and classify melanoma skin cancer. Hence, another performance improvement technique should be applied to get the desired accuracy, and the researcher applied U-Net segmentation to the training and validation dataset, and the study conducted the second experiment. The details of the second experiment is given below.

Table 3. Training Details of the Proposed Model after Applying U-Net Segmentation

Model	**Optimizer**	**Epochs**	**Learning Rate**	**Training Accuracy**	**Validation Accuracy**	**Training Loss**	**Validation Loss**	**Number of correctly classified**	**Number of misclassified**
EMCDC	Adam	100	0.001	93.25%	92.87%	18%	19.4%	2949	234



(a)

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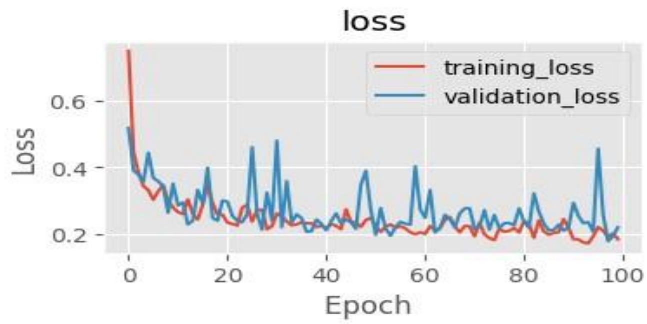

(b)

Figure 8: (a) Training and Validation Accuracy of the Proposed Model, (b) Training and Validation Loss of the Proposed Model after Applying U-Net Segmentation

Table 4. Performance Measure of the Proposed Model after Applying U-Net Segmentation

Classes	**Precision**	**Recall**	**F1-score**	**Support**
Benign	0.94	0.92	0.93	1651
Malignant	0.92	0.93	0.92	1532
Accuracy			0.93	3183
Macro avg	0.93	0.92	0.92	3183
Weighted avg	0.93	0.92	0.92	3183

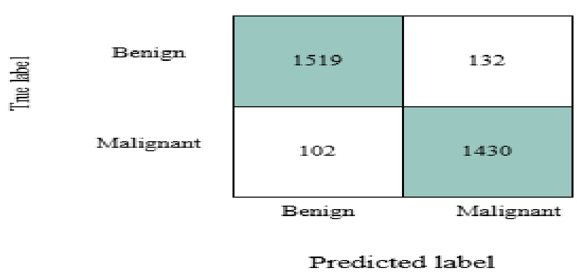

Figure 9: Confusion Matrix of the Proposed Model after Applying U-Net Segmentation.

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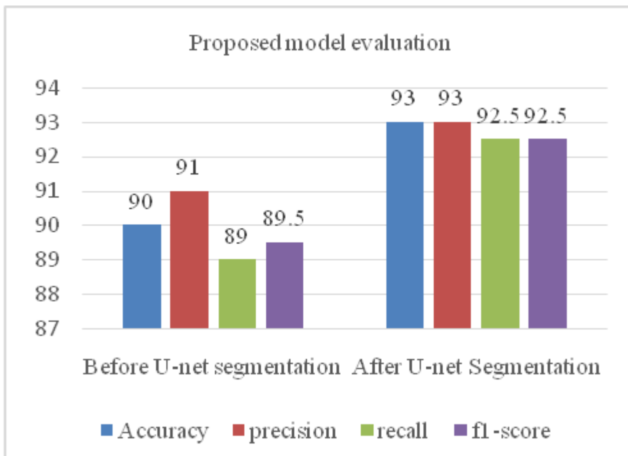
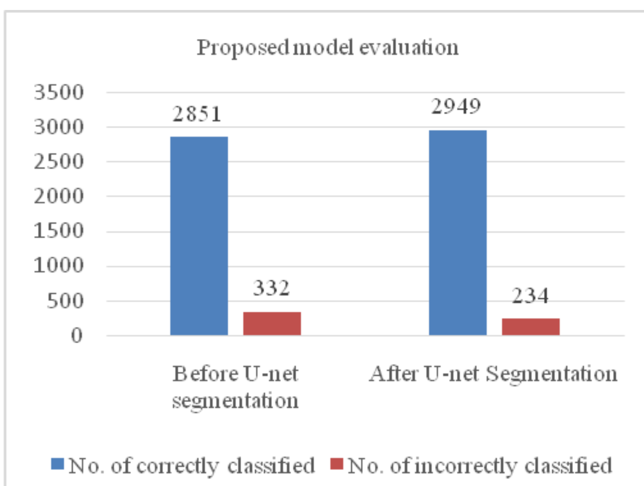
D. Discussion

Automatic melanoma skin cancer segmentation is a crucial topic in the medical domain and a critical counterpart in the computer-aided diagnosis paradigm. Thus, in this study, the researcher shows the power of U-net segmentation architecture in improving the classification accuracy of melanoma skin cancer. As the experiment result shows, the proposed U-net segmentation architecture is a powerful image segmentation architecture due to its flexibility, optimized modular design, and success in all melanoma skin cancer image modalities. As depicted in figure 10 below, before applying the U-net segmentation to the model, the classification accuracy was 90%. While, after applying U-net segmentation to the input image, the model performance increases to 93% of classification accuracy.



(a)



(b)

Figure 10: (a), (b), Proposed Model Performance Evaluation Before and After Applying U-Net Segmentation

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As depicted in the above figure 10, the number of misclassified images decreased from 332 to 234 and the number of correctly classified images increased from 2851 to 2949. The application of the U-net segmentation architecture to the input image accurately segments the desired feature target and also improves the accuracy of melanoma skin cancer.

E. Comparison with other State-of-art Models

Various studies have been done in the past to detect and classify melanoma skin cancer as benign and malignant, however, fusion of deep learning algorithms for feature extraction and U-Net segmentation for segmentation is a novel approach to detect and differentiate melanoma skin cancer. As compared to the previous studies, the proposed method achieved a remarkable high accuracy in the detection and classification of melanoma skin cancer. Table 5 shows the proposed method with the existing approaches discussed in the literature review part.

Table 5. Comparison of the Proposed Modelwith OtherState-of-Art Models

Author	**Method Used**	**Accuracy** (%)
Chaandran et al. [1]	▪ LeNet, VGG16, and SVM	91
Hiam et al. [7]	▪ SVM	92.1
Kavitha et al. [9]	▪ CNN	84.32
Kakularam and Rama [10]	▪ CNN, and Decision Tree	85.65
Simon Kalouche [11]	▪ CNN	78%
Atheer et al. [12]	▪ ResNet, Xception, and VGG16 with stacking of RE, NN,KNN, and LR	90.9
Naga et al. [13]	▪ CNN	92
Taher et al. [15]	▪ AlexNet	87.1
Proposed Method	▪ U-Net Segmentation, fusion of ResNet-50 and VGG16	93

F. Conclusion and Future Work

A. Conclusion

In this study, the researcher proposed a novel approach to detect and classify melanoma skin cancer as benign or malignant. The study follows an experimental research approach, which involves dataset preparation for training and evaluating the melanoma skin cancer classification. The method leverages the Feature fusion of VGG16 and ResNet-50 deep

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learning models. At first, the researcher extracts features from training images using the VGG16 and ResNet-50 models, and features are fused together using global average pooling and fed to the dense layer. Without applying U-net segmentation, the modelhas achieved 90% classification accuracy. Secondly, by integrating feature fusion of VGG16 and ResNet-50 deep learning models with U-net segmentation, the model achieved a significant improvement in accuracy (93% of classification accuracy). The investigation demonstrated that applying the appropriate segmentation method to the image can accurately delineate lesion boundaries and highlight crucial diagnostic areas. Thus, applying u-net segmentation improves the classification accuracy of testing images by 3%. This indicates that the proposed method (EMCDC)is effective in improving diagnosis precision and reliability compared to traditional approaches. The method advances melanoma skin cancer detection through the fusion of features from multiple deep learning algorithms and paves the way for a more accurate and efficient dermatological diagnostic tool.

B. Future Work

In the future**,** the study will fuse features of multiple deep learning algorithms with large amounts of training data to develop a generalized model that can classify all cancer types and boost the performance of the model. In addition, the researcher will develop the model as a mobile application so that it can be easily accessible by many users. Furthermore, integrating clinical information into the dataset will further improve the performance of the model

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