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ORIGINAL RESEARCH

Improving Skin Lesion Segmentation Accuracy in Dermatological Imaging using SegNet: A Deep Learning Approach for Enhanced Diagnostics

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Abstract

Melanoma is one of the most severe forms of skin cancer that needs to be detected early and accurately. A new area of study called Computer-Aided Diagnosis or Detection (CAD) for skin lesion analysis has proved effective for reducing the difficulty and expense of skin cancer screening. We proposed a fully deep-learning approach using the SegNet architecture. This proposed methodology aims to improve the precision of skin lesion segmentation, which is an essential part of dermatological diagnosis. We gathered the ISIC 2016 and 2017 datasets and used the pictures for validation, testing, and training. A comparative study is done with current models (U-Net). We assessed some critical parameters, including accuracy, precision, recall, the intersection over union (IoU), and the dice coefficient. For our model, we also determined the binary cross-entropy. The SegNet architectural model has an accuracy of 91.93%, an IoU of 90.32%, a dice coefficient of 71.68%, a precision of 83.54%, a recall of 91.59%, and a precision of 83.54%. We used aggressive techniques like voting or averaging. By merging SegNet and UNet predictions, we obtained an ensemble result. This gives us a more reliable solution for jobs like picture segmentation and helps us to decrease overfitting. We contrast our testing image IoU, recall, precision, accuracy, and dice coefficient values with those of other models. Our suggested model provides more precision in skin lesion segmentation, offers a more effective treatment for skin cancer, and significantly contributes to detection.

1 | INTRODUCTION

Skin lesions are deviations from the usual appearance of the skin, which can appear in diverse forms, colours, sizes, and textures. They can originate from various factors, such as infections, inflammation, trauma, allergic reactions, and underlying medical disorders. Comprehending the attributes of various skin lesions is essential for accurate diagnosis and therapy. Ensuring good skin health and general well-being require timely recognition, correct diagnosis, and proper care. In the USA skin cancer stands out as a prevalent malignancy, representing one of the most frequently encountered appearance of cancer. Melanoma, a kind of cancer known for its extreme mortality, is one of the most serious cancers. In the United States, an annual confirmation of 5.4 million new cases occurs without fail [1].

By reducing the process's expenditure and complexity, CAD has the potential to revolutionize skin cancer screening. To enhance the accuracy of skin lesion segmentation, a critical component of dermatological diagnosis, we specifically propose an entirely deep-learning approach utilizing the SegNet architecture. Validation, testing, and training are conducted utilizing datasets obtained from ISIC 2016 and 2017. An analysis of contemporary models, including U-Net, is also performed as a part of this process. The findings of our study indicate that the methodology we have suggested yields enhanced accuracy in the segmentation of skin lesions, thereby presenting a more viable therapeutic approach for skin cancer and making a substantial contribution to the field of detection.

Dermoscopy is useful in enhancing the reliability and effectiveness of diagnosing and categorizing skin lesions in the context of skin lesion segmentation. On a dermoscopy picture, skin lesion segmentation refers to the process of separating the area of interest(lesion) from the surrounding healthy skin. Dermoscopy, a method for detecting and classifying cancers of the skin such as melanoma, cancer of the basal cell, and cancer of the squamous cells, is also effective in distinguishing other pigmented and non-pigmented skin conditions. Because of the inherent visual similarities of many skin diseases e.g., melanoma, nevus, and seborrheic keratosis, even dermoscopy professionals have difficulty identifying for them. Some of their techniques have generated reliable outcomes and positively impact human performance because of the advanced machine learning technology [2].

Including Thresholding-Base, Region-Base, Edge-Base, Clustering, Active contour models, and conventional supervised methods, various techniques for segmenting skin lesions have encountered challenges and limitations when applied to extensive datasets, highlighting the complexities associated with addressing this formidable problem [3]-[4]. Machine learning approaches include convolutional neural networks (CNNs), support vector machines (SVMs), and ensemble models. These approaches displayed outstanding segmentation performance, demonstrating machine learning's ability to outline lesion borders properly [5].

Deep learning algorithms for segmentation based on semantics, on the contrary, have recently been created and have shown promising results. For example, Convolutional Neural Networks for Biomedical Image Segmentation is a deep learning architecture created exclusively for biomedical image segmentation applications such as skin lesion segmentation [6]. The architecture known as U-Net has been widely utilized in biomedical image segmentation applications such as skin lesion segmentation. Its accuracy in separating skin lesions has made it an attractive choice in the field [7]. FCN (Fully Convolutional Networks) technique has had an important impact on semantic segmentation, especially its use in skin lesion segmentation. FCNs have shown promise in accurately segmenting skin lesions and other fine-grained features in medical pictures by enabling end-to-end pixel-wise predictions [7]. The mask branch of Mask R-CNN constitutes a fully convolutional network (FCN), which ingests a RoI as its input and generates a binary mask for every class. This FCN is formed up of an order of convolutional and upsampling layers that gradually raise the spatial resolution of the input RoI and refine the segmentation mask. The mask branch uses the same backbone network as the Faster R-CNN architecture, enabling end-to-end training [8].

The failure of Thresholding-Base, Region-Base, Edge-Base, Clustering, Active contour models, and typical supervised algorithms on big datasets shows the complexity of skin lesion segmentation. Biomedical image segmentation's U-Net design lacks precision and performance. Researchers require a better skin lesion segmentation approach. Dermatological diagnosis requires skin lesion segmentation, which our SegNet-based deep-learning technique does. Our method has 91.93% accuracy, 90.32% IoU, 71.68% dice coefficient, 83.54% precision, 91.59% recall, and 83.54% precision. An ensemble of SegNet and UNet predictions enhanced picture segmentation and minimized overfitting. Our model improves skin lesion segmentation, cancer diagnosis, and treatment.

This paper made the contributions, which are summarized below:

- To improve the accuracy of skin lesion segmentation, proposed a framework based on the SegNet architecture model.
- Used two distinct neural network architectures SegNet and U-Net with the use of an ensemble technique we can understand more intricate correlations between the image's pixels, producing more accurate segmentation results.
- For segmenting skin lesions; each has a distinct dataset for the training, Test, and Validation sets. Research also includes methods for pre-processing, picture data augmentation, batch normalization, standardization, and post-processing.
- The segmentation models for SegNet and U-Net are displayed in the graph along with their accuracy and loss during training and validation.
- Higher performance has been achieved when we compared our proposed model to other models.

2 | RELATED WORKS

Much research has been done to develop methods for automatic lesion segmentation as lesion accuracy classification depends on the reliability of the lesion segmentation. These methods can be threshold-based, based on edge detection, based on region growth, etc. One of the latest methods explains the segmentation as a curve evolution using deformable models. Sadeghi et al. [9] used to detect the edges of lesions and cyclic graphs developed binary edge masks of lesions. It was a new method designed to detect and visualize pigment network structures in dermoscopic images. The method includes pre-processing, image enhancement, and edge detection. The resulting binary edge image was converted to a graph and feature patterns were extracted. That chart was then classified based on the density ratio. The method achieves an accuracy of 94.3% over 500 frames. Segmentation algorithms based on thresholding were used depending on the quantitative differences between the skin lesions and surrounding normal skin. The area of the lesion was defined by Garnavi [10] using histogram thresholding and the cie-xyz colour space. This research describes a unique automatic segmentation system for the diagnosis of melanoma which combines color space analysis with clustering histogram thresholding. Using the x and colour channels, Algorithm tested on thirty high-resolution dermoscopy images and obtained an accuracy of almost 97%. The approach demonstrates its effectiveness and superiority in the segmentation of skin lesions by overcoming two state-of-the-art approaches. The study highlights the need for improved colour space in melanoma diagnosis. Segmentation was performed using statistical pooling of regions in various thresholding techniques [11]. Advances in leather imaging technologies and image processing techniques have led to increased interest in computer-assisted melanoma diagnostics, where automatic border detection is decisive accuracy. An improved systematic review of the state-of-the-art border detection techniques. This paper presents a pre-processing approach to improve lesion segmentation algorithms by enhancing the colour information and image contrast. It combines two different segmentation algorithms: one analyzes the image background iteratively pixel measurement without damage and the other uses cooperative neural networks for edge detection. Experiments on 100 dermoscopic images showed both techniques provided good segmentation performance with an emphasis on the importance of highlighting colours in this process. Machine-learned methods have gained popularity for segmentation tasks in clustering, pattern recognition techniques, and controlled classification producing excellent results in skin perceptron classifier to determine visual function extraction for segmentation. Calculated histogram and used painter of the initial clusters which were then submitted to a fuzzy c-means clustering method for boundary segmentation. The neural network was constructed by Schaefer et al. [12] characteristics of the lesions in the training sets. Jafari [13] created a segmented mask using a fully connected CNN, which took longer to train. This paper suggests an in-depth neural network-based method for the accurate detection of suspicious moles and lesions in clinical images. The method used pre-processed images and convolutional neural networks to assign pixels to lesion or normal classes. The method achieves an accuracy of 98.7% and a sensitivity of 95.2% inches segmentation of lesion areas, surpassing other state-of-the-art algorithms on a qualitative and quantitative scale assessment. The top three posts of 2017 have been challenged to create precise and accurate segmentations and apply deep learning architectures for skin lesion segmentation [14] and [15]. Automatic segmentation of melanoma from surrounding skin was key in computerized dermoscopic analysis. However, melanoma has a varied appearance, irregular edges, low contrast, and internal skin features that created the segmentation demand. The researchers designed the framework using deep fully convolutional-deconvolutional neural networks (cdnn) to automatically segment skin lesions in dermoscopic images. Emphasis was placed on the design of a suitable network architecture and effective training strategies. Compared to existing deep learning approaches, the method provides a simpler network design with fewer pre- and post-processing stages. In terms of lesion segmentation accuracy, experimental findings indicated that our proposed system outperforms other prior art approaches. Rashika Mishra's paper presents a method using deep convolutional neural networks for extracting lesion regions from dermoscopic images. The method has a high accuracy of 92.8% and a better Jaccard index than traditional Otsu thresholding The segmented images can be analyzed to classify them into malignant or benign tumours [16]. In this study, FCN UNET-based segmentation methods are used for skin image analysis and segmentation. The improved U-Net model outperforms the existing model with the smallest difference in the average Jaccard index, and future work will focus on integration [17]. This article presents the development of U-Net CNN for image segmentation in dermatology datasets. This architecture improves performance by using a pre-trained school and adaptive pooling techniques. Compared with the existing CNN architecture, this method has better stability and performance, with 92% accuracy for training data and 98\% accuracy for testing data. Factors affecting network performance are examined [18].

In this paper, we proposed a deep-learning approach using SegNet architecture to improve skin lesion segmentation accuracy in dermatology diagnosis. The SegNet architectural model achieved a precision of 91.93%, an IoU of 90.32%, a dice coefficient of 71.68%, a precision of 83.54%, a recall of 91.59%, and a precision of 83.54%. The model also determined the binary cross-entropy. The SegNet architecture is a promising approach that provides greater accuracy in skin lesion segmentation, more effective treatment for skin cancer, and significant contributions to detection. We also apply aggressive strategies like averaging and voting. We generated an ensemble result by combining the predictions from SegNet and U-Net. This reduces overfitting and provides a more dependable solution for tasks.

3 | Methodology

Figure 1. represents our entire skin lesion segmentation procedure. First, obtain data that includes both the ground-truth and original images. Each patient sample's four data categories are divided into three regions of the dataset: the training set, test set, and validation set. We carry out certain preparation operations in our approach, expanding the dataset by adjusting copies of preexisting data and tailoring a model created with the SegNet architecture framework in mind. Activate every parameter and enhance the model's performance. This process, known as testing, consists of quantitative performance and prediction. IoU, dice coefficient, precision, and recall metrics quantify performance. For prediction, a final set of image samples was acquired.

3.1 | Dataset

The ISIC difficulties are now a driving force for melanoma cancer research. ISIC provides professionally annotated, biopsy-proven collections of digitized, high-resolution images of skin lesions from around the globe. The objective is to progress the study in this area to offer automated Computer Aided Diagnosis (CAD) instruments for identifying cancers, such as melanoma and all forms of skin cancer.

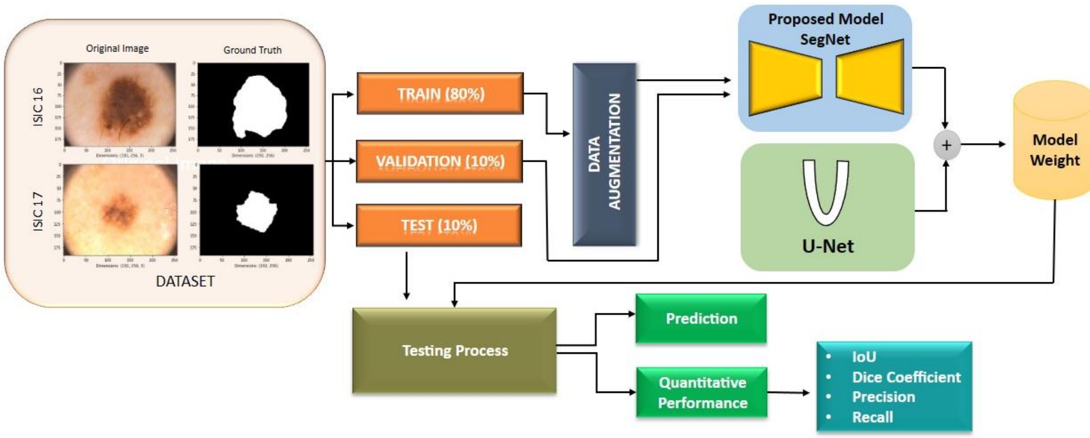

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Figure 1: Presenting the overall process in our proposed system

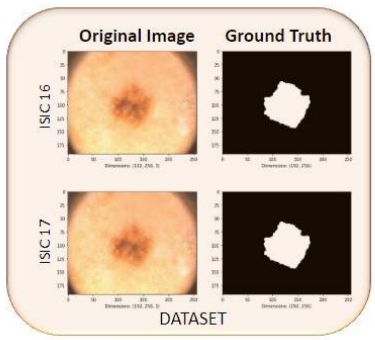

Figure 2: ISIC Dataset 2016 and 2017 contains the original image and ground truth image

Table 1. Dataset of ISIC 2016 and 2017 images

Dataset of	Total	Before Preprocessing (Training)	After Training	Validation Set	Test Set
ISIC 2016	900	379	1516	155.6	155.6
ISIC 2017	2000	600	2400	240	240
Combine (16+17)	2900	979	3916	391.6	391.6

Additionally, this group hosts annual skin lesion challenges to raise awareness of skin malignancies and to motivate additional researchers to work together to improve CAD algorithm diagnosis. Along with a training and validation set for model training in the ISIC challenges 2016 and 2017 datasets [19] a testing set is given for skin lesion segmentation prediction purposes. Table 1 represents the summary of the ISIC dataset 2016 and 2017.

In Table 1 there are 900 total photos in the ISIC 2016 dataset. Three hundred seventy-nine training photos were used before preprocessing. We are adding 1516 photos to our training dataset after it is finished. The test and validation sets are identical in this case because 10\% of the training set is present in both. There are either 155.6 or 157 photos in the validation and test sets. The ISIC 2017 dataset then has a total of 2000 photos in it. The training image count is 600 before preprocessing. We are adding 2400 photos to our training dataset after it is finished. The test and validation sets are identical in this case because 10% of the training set is present in both. There are 240 image sets in the validation and test sets. After merging the ISIC 2016 and ISIC 2017 datasets, we obtained 2900 photos, of which 979 were preprocessed images. Following training, we received

3.2 | Preprocessing

We first obtain the image using non-invasive methods, including spectroscopic imaging, magnetic resonance imaging, ultrasound, dermoscopy, optical coherence tomography, and x-rays. Usually, these photos have distracting elements such as skin surfaces, hair, and light reflection from asymmetric lighting. We should apply the preprocessing technique step for the input image to eliminate any adverse effects and obtain a more transparent visual image. The segmentation results are significantly affected when hair, considered noise, is removed from skin images. We use the color spaces HSV (Hue, Saturation, Value) and RGB (Red, Green, Blue). In addition, we turn the RGB picture into a grayscale one. By making the photos the same size (256×256), we successfully trained our deep model. In the medical industry, image inpainting is crucial in preprocessing methods to extract specific areas from images and repair damaged or missing data.

3.2.1 | Image Data Augmentation

Creating new training examples from preexisting ones is known as image data augmentation. It produces various processes, such as flips, random rotation, shifts, shear, etc., or numerous process combinations. Along with cropping and resizing the image, it modifies brightness and contrast. In this case, we employ image flipping in both the vertical and horizontal directions along the x and y axes. Random rotation is another technique that yields an integer number and permits the images to rotate arbitrarily through any degree between 0 and 360 degrees. We also use this picture augmentation to get rid of the overfitting problems. To smooth the image and lower the noise, we employ Gaussian noise. Statistical noise with a Gaussian (normal) distribution, or noise values distributed in a normal Gaussian manner, is referred to as Gaussian noise.

3.2.2 | Batch Normalization

Neural network training typically uses batch data, a collection of input data. The model is scaled using the normalization process using the lowest and maximum values. In general, batch normalization is an approach that is used between a neural network's layers as opposed to the raw data itself. Instead of using all the data, it uses the mean. It facilitates faster training, which makes it simpler to learn the data. Every convolutional neural network in the suggested network is followed by batch normalization. The

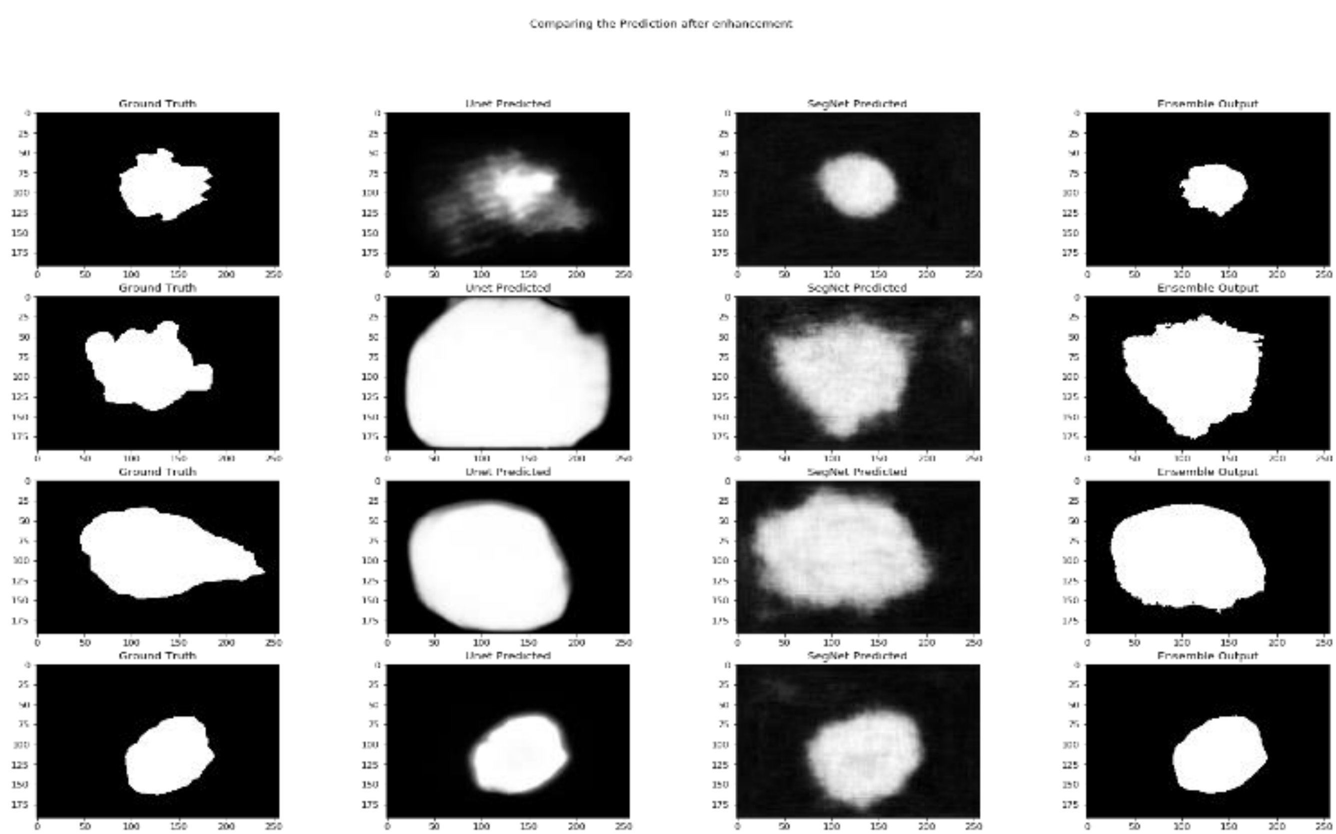

Figure 3: Represent the ensemble prediction. The first row indicates the ground truth image, the second row is the U-Net predicted image, the third row is the SegNet predicted image and the last row is the ensemble output.

entire suggested network architecture consists of roughly 25 batch normalization layers.

3.2.3 | Standardization

Standard normal distribution, which is characterized as a distribution with a mean of 0 and a standard deviation of 1, is the basis for standardization. Every measurement is changed to the metric system. Here, we dispersed the data as a standard deviation and used this to make the data easier to use and understand.

3.3 | Post Processing

We will employ thresholding as a basic post-processing approach. utilizing a threshold of 0.7, an arbitrary number selected from a range of practically tested values. Any pixel value more than 0.7 will be converted to 1, and any value less than 0.7 will be converted to 0. Moreover, this will get rid of a lot of grey pixels.

Bagging (Ensemble Prediction)

Bagging is a method that enhances overall performance and robustness by merging the predictions from several models. Another name for it is bootstrap aggregation. In this work, we suggest SegNet as our new model, whereas U-Net is our current model. In this study, we combine these two models to improve prediction. The dataset should first be randomly divided, and each dataset should then be trained separately using the SegNet and U-Net architectural models. To enhance diversity during training, we can use data augmentation techniques such as random rotation, vertical flip, horizontal flip, and Gaussian noise. We can save each model's weights once this training is finished, get a prediction for the input image from each of the ensemble's SegNet and U-Net models, and then merge the projections with an appropriate aggregation technique. Here are two approaches to aggression: voting schemes and averaging.

- Voting: A majority vote is required to choose the final class for classification jobs.
- Averaging: Take the average of each model's expected outputs or probability.

We can use post-processing methods. Using a validation or test set, the ensemble's performance is then assessed using relevant measures, such as IoU, dice coefficient, precision, recall, and accuracy. Bagging with SegNet and U-Net architectures lessens overfitting and improves the ensemble's capacity for generalization. Integrating several models' advantages offers a more reliable solution for applications like image segmentation.\\

Figure 3 describes the first row as the ground truth image, the second row as the predicted image of the U-Net model, the third row as the predicted image of the SegNet model, and the last row as the ensemble output.

3.4 | Model Architecture (SegNet)

SegNet is a deep convolutional encoder/decoder architecture used for image segmentation. The encoder and matching decoder networks that comprise this basic trainable segmentation architecture are followed by a pixel-wise classification layer. It has been applied to the segmentation of biomedical images. This segmentation model is semantic. CNN architecture first extracts all visual features for semantic segmentation and then uses these features to determine the target image. The encoder and decoder are the two sections that make up this system. In this case, the filter width affects how quickly the encoder subsamples or reduces the image size. Convolution, pooling, dropout, concatenation, and ReLU (Rectified Linear Unit) layers are most important in this model. Image features are extracted using the convolutional layer in the encoder section. The pooling layer in the decoder section has the most impact on reducing the size of the input image. This layer significantly reduces the image size based on the selected neighborhood parameters. Pooling layers with high neighborhood values will make the edge information softer. Concatenation is commonly used to build skip connections in SegNet architecture, which is utilized for semantic segmentation. This is because these designs frequently have a" symmetric" structure in which the final segmentation map is created by first downsampling the feature maps and then upsampling them. Skip connections based on concatenation aid in maintaining spatial information during upsampling. ReLU, a nonlinear activation function, is used to solve memory problems. Dropout layers prevent overfitting and address the issue of neurons learning proportionally and cooperating. Figure 4 represents the proposed SegNet architecture model.

4 | Experiment (Local PC Description) & Evaluation Metrics

Evaluation metrics based on pixels are used to determine the quality of machine learning models. The critical metric is IoU, mentioned in equation (1), which shows the overlap between the ground truth box and the projected box. The dice coefficient mentioned in equation (2) gauges the accuracy of pixel-by-pixel segmentation. Precision is mentioned in equation (3), which evaluates the accuracy of optimistic predictions. Recall is mentioned in equation (4), which assesses the comprehensiveness of favorable predictions. At last, accuracy is mentioned in equation (5), which indicates the distance from actual or acceptable values.

$$IoU = \frac{TP}{TP + FP + FN} \dots\dots\dots (1)$$

$$Dice = \frac{2TP}{(TP + FP) + (TP + FN\ )} \dots\dots.\dots (2)$$

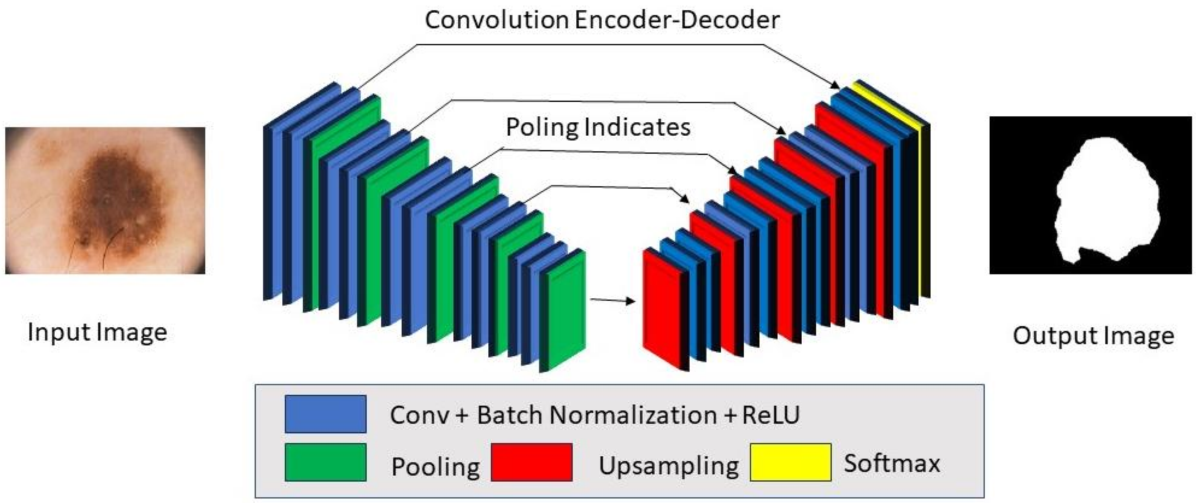

Figure 4: SegNet Architecture Model

$$Precission = \frac{TP}{TP + FP} \dots\dots\dots (3)$$

$$Recall = \frac{TP}{TP + FN} \dots\dots\dots (4)$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \dots\dots\dots (5)$$

Binary cross-entropy loss / log loss

A popular loss function in binary classification issues is binary cross-entropy loss, sometimes referred to as log loss. Between the genuine classes and the anticipated classes, it computes the cross-entropy loss (6).

$$logloss = \frac{1}{N} \sum_{i}^{N} \sum_{j}^{M} y_{ij} \log(P_{ij}) \dots\dots\dots (6)$$

Here

1. N is the number of rows
2. M is the number of classes.
3. y_i is the true label for the i-th instance (either 0 or 1).
4. Pi is the predicted probability that the i-th instance belongs to class 1.

5 | RESULT ANALYSIS

5.1 | Curve Result

Figure 5. graph shows the accuracy and loss during training and validation for the SegNet and U-Net segmentation models. The training loss and accuracy curves for both models show a general downward and upward trend. SegNet's training loss and validation loss curve begins at around 0.9 and 0.8 and decreases gradually throughout the training process. During the training and training accuracy phase, SegNet's validation accuracy curve progressively rises from 0.45, and the training accuracy curve begins at around 0.5, which progressively increases the training procedure. U-Net training loss curve begins at around 0.225, and validation loss for U-Net starts from the middle of 0.4-0.5 and decreases gradually throughout the training process. U-Net training accuracy curve begins at around 0.750, and the training accuracy curve starts at around 0.3 to 0.4 and progressively rises during the training procedure.

Table 2: Experiment (Local PC Description) \& Evaluation Metrics

Component	**Model**
Processor (CPU)	Ryzen 5
Graphics Card (GPU)	Zotac 1600 Gaming Super
Memory (RAM)	8GB
Storage HDD	1TB
Motherboard	Gigabyte B450M S2H
Power Supply Unit (PSU)	550W, Cooling Master
Cooling System	Air Cooling (Ryzen)

5.2 | Quantitative Result

Table 3 presents an assessment metrics table for skin lesion segmentation using two distinct neural network architectures, namely SegNet and U-Net, each with a separate dataset for the Train, Test, and Validation sets. Both SegNet and U-Net are fully convolutional neural networks (CNNs). For every metric and dataset split, compare and determine which SegNet or U-Net achieves the greatest values.

SegNet had the most excellent IOU values on the train set, at 93.80%, while U-Net obtained the highest Dice Coefficient values, at 81.78%. This implies that U-Net can properly segment items in the training data. Comparing SegNet's results to U-net, the most significant values—92.41%, 96.62%, 96.60%, and 19.63%—were obtained for precision, recall, accuracy, and loss. This shows that SegNet can effectively decrease the error of its predictions on the training data, categorize pictures, and detect actual and all-positive situations. On the Test Set, when compared to U-Net and SegNet, U-Net achieved the greatest IOU, Dice Efficiency, and Accuracy values, at 91.73%, 83.61%, and 89.49%, respectively. On the other hand, SegNet has achieved the greatest Recall, Accuracy, and Loss values at 91.59%, 91.93%, and 26.45%. In the validation test, U-Net outperformed SegNet, achieving the greatest IOU, dice coefficient, and precision values of 91.07%, 82.57%, and 93.29%. In contrast, SegNet obtained the highest recall, accuracy, and loss values of 87.92%, 91.67%, and 26.59%, respectively.

5.3 | Qualitative Result

The segmentation of the suggested method was demonstrated by applying the SegNet Architecture framework to segment each image from the dataset (ISIC 2016 and 2017). Figure\ref{fig:5} presents a few exemplary samples of the results found for this particular dataset. This figure has four columns. The original picture and ground truth are displayed in the first two columns. In the following

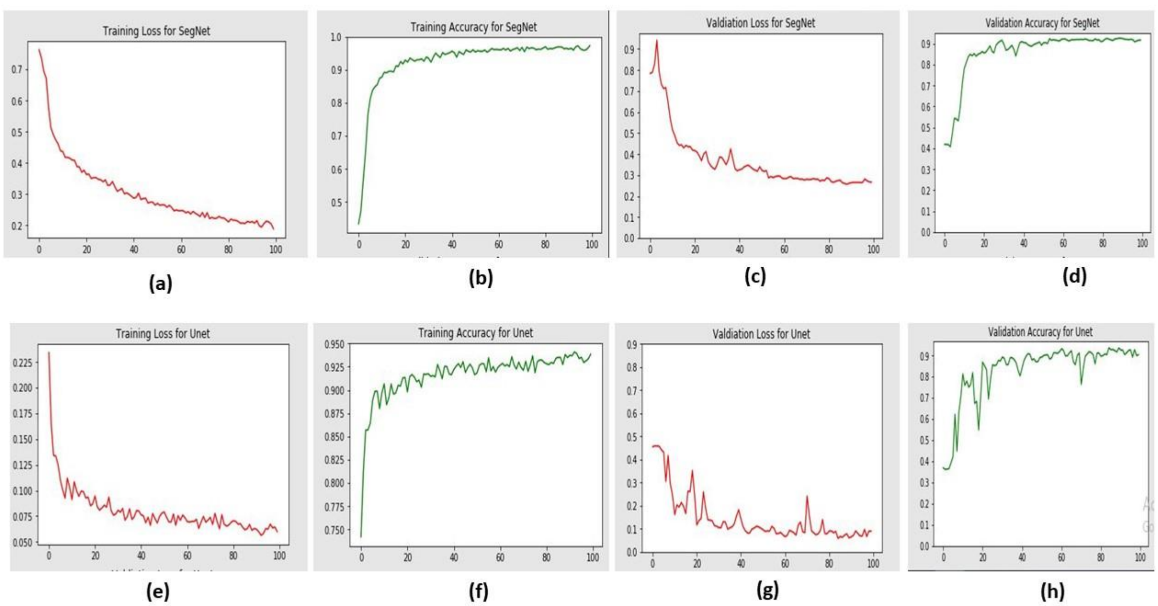

Figure 5: Model training time performance first row (a), (b), (c), (d) present Training Loss, Training Accuracy, Validation Loss, Validation Accuracy for SegNet and Second row (e), (f), (g), (h) present Training Loss, Training Accuracy, Validation Loss, Validation Accuracy for U-Net.

Table 3: Represent the Performance of a SegNet & U-Net model Evaluation for Skin Lesion Segmentation

	One Train Set		**One Test Set**		**One Validation Set**	
	SegNet	UNet	SegNet	UNet	SegNet	UNet
IOU (%)	93.80	91.19	90.32	91.73	90.98	91.07
Dice Coef (%)	75.41	81.78	71.68	83.61	73.65	82.52
Precision (%)	92.41	90.25	83.54	89.49	88.94	93.29
Recall (%)	96.62	79.13	91.59	83.20	87.92	78.51
Accuracy (%)	96.60	90.94	91.93	91.83	91.67	90.32
Loss	19.63	8.81	26.45	8.27	26.59	8.93

the segmentation map produced by SegNet, our proposed model. As can be seen from this Figure 5 there is a good agreement based on observation among the results obtained by the proposed method, U-Net, and ground truth. Success cases of our model over SegNet show the second, third, and fourth rows (The U-Net approach contains too many false positive pixels and cannot correctly extract the margins of lesions. The reduction in wrong negative interstices is displayed in Figure 5(b), (c), and (d), highlighting the reduced proportions noticed in the results produced by our model). Figure 5(a) illustrates the failure cases of the proposed network over Segnet in the first row. (U-Net has correctly detected the lesion's region and has fewer false negative gaps than SegNet). In the last row, Figure 5(e), both SegNet and U-Net cannot properly detect the lesson's area, but the SegNet model has shown a better result than the U-Net.

5.4 | Result Comparison with other models

The proposed model (seg-net) shows a comprehensive improvement in various metrics, indicating its effectiveness in the given task compared to DenseNet121, ResNet50, VGG19, Exception, and EfficientNetB3.A detailed comparison highlights the excellent test performance. The proposed model (segnet) outperforms all existing models and achieves an accuracy of 91.83%, precision (83.54%), recall of 91.59%, IOU (90.32%), and Dice Coef (71.68%) across various metrics, indicating its potential as a robust and accurate solution compared to existing models cited in [19]. These findings underline the proposed model's effectiveness in the study's specific context.

6 | CONCLUSION

This research presents an efficient method for skin-lesion

Table 4: Comparison analysis between other models and our proposed model.

Model	Accuracy	IOU	Dice Coef	Precision	Recall
DenseNet [19]	41.00	–	–	20.00	
ResNet50 [19]	40.00	–	–	20.00	71.00
VGG19 [19]	56.00	–	–	20.00	41.00
Xception [19]	44.00	–	–	19.00	59.00
EfficientNetB3 [19]	53.00	–	–	22.00	58.00
Proposed	91.83	90.32	71.68	83.54	91.59

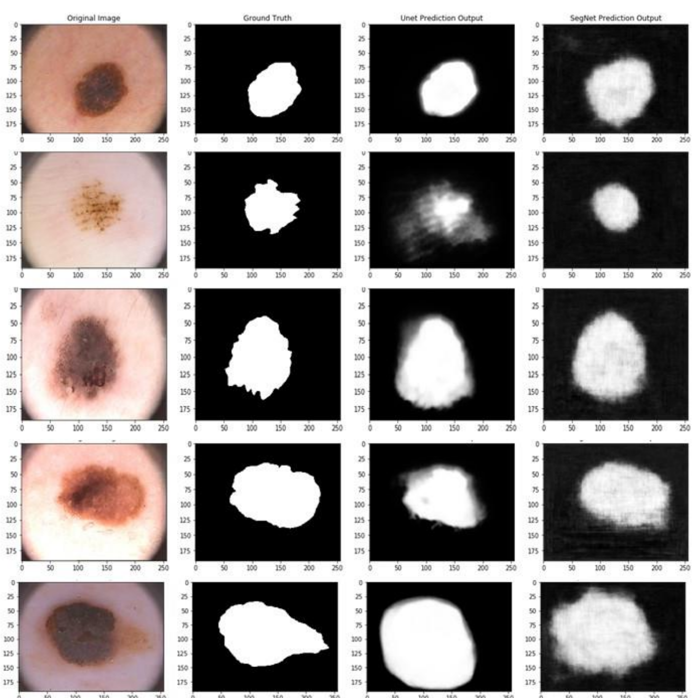

Figure 6: Examples of our method's performance on the 2016 and 2017 ISIC challenge datasets for skin lesion segmentation. The first column contains the Input images, the second column is the ground truth mask, the third column is the U-Net and the last column is the prediction of the proposed method.

segmentation. Here, SegNet: A Deep Learning Approach for Enhanced Diagnostics to increase skin lesion segmentation accuracy in dermatological imaging. We know that skin cancer is the most common type worldwide and that melanoma is becoming more and more threatening to other individuals. For better results in treatment, an early cancer diagnosis is crucial. Segmenting skin lesions is an essential first step in creating a computer-aided skin cancer diagnosis system. The skin lesion segmentation in this diagnostic is enhanced by the SegNet architecture, which is entirely dependent on a deep learning process. Further, utilizing the SegNet architecture, we have effectively created a skin lesion segmentation method in this study. The ISIC 2016 and 2017 datasets were gathered. In addition to finding the validation set, we have trained and evaluated the pictures. U-Net architecture is our current approach, while SegNet architecture is our training method. In the SegNet architecture test set, we observed 91.93% accuracy, and in the U-Net architecture test, 91.83% accuracy. We contrast that architecture's accuracy. Additionally, we included some curves utilizing the Unet and SegNet architectures to display the loss and accuracy for the training and validation images. Finally, we finished our segmentation successfully. In the future, we plan to increase the dataset, collaborate with individuals from other regions and apply different network architectures such as Recurrent Neural Network (RNN) and also use various models, such as DenseNet121, ResNet50, and VGG19, and aggregate the findings to uncover more precise results that will aid in identifying the accurate issue for more effective therapy.

REFERENCES

[1] Rogers, H. W., Weinstock, M. A., Feldman, S. R., & Coldiron, B. M. (2015). Incidence estimate of nonmelanoma skin cancer (keratinocyte carcinomas) in the US population, 2012. JAMA dermatology, 151(10), 1081-1086.

[2] He, K., Zhang, X., Ren, S., & Sun, J. (2015). Delving deep into rectifiers: Surpassing human-level performance on ImageNet classification. In Proceedings of the IEEE International Conference on Computer Vision (pp. 1026-1034).

[3] Silveira, M., Nascimento, J. C., Marques, J. S., Marçal, A. R., Mendonça, T., Yamauchi, S.,& Rozeira, J. (2009). Comparison of segmentation methods for melanoma diagnosis in dermoscopy images. IEEE Journal of Selected Topics in Signal Processing, 3(1), 35-45

[4] Celebi, M. E., Iyatomi, H., Schaefer, G., & Stoecker, W. V. (2009). Lesion border detection in dermoscopy images. Computerized medical imaging and graphics, 33(2), 148-153.

[5] Yu, L., Chen, H., Dou, Q., Qin, J., & Heng, P. A. (2016). Automated melanoma recognition in dermoscopy images via intense residual networks. IEEE transactions on medical imaging, 36(4), 994-1004.

[6] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18 (pp. 234-241). Springer International Publishing.

[7] Long, J., Shelhamer, E., & Darrell, T. (2015). Fully convolutional networks for semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 3431-3440).

[8] Mask, R. C. N. N., He, K., Gkioxari, G., Dollár, P., \& Girshick, R. (2017). Mask r-cnn. In Proceedings of the IEEE International Conference on Computer (pp. 2961-2969).

[9] Sadeghi, M., Razmara, M., Lee, T. K., & Atkins, M. S. (2011). A novel method for detection of a pigment network in dermoscopic images using graphs. Computerized Medical Imaging and Graphics, 35(2), 137-143.

[10] Garnavi, R., Aldeen, M., Celebi, M. E., Bhuiyan, A., Dolianitis, C., \& Varigos, G. (2010). Automatic segmentation of dermoscopy images using histogram thresholding on optimal color channels. International Journal of Medicine and Medical Sciences, 1(2), 126-134.

[11] Kingravi, H. A., Iyatomi, H., Aslandogan, Y. A., Stoecker, W. V., Malters, J. M., Grichnik, J. M., & Celebi, M. E. (2008). Border Detection in Dermoscopy Images Using Statistical Region Merging.

[12] Schaefer, G., Rajab, M. I., Celebi, M. E., & Iyatomi, H. (2011). Color and contrast enhancement for improved skin lesion segmentation. Computerized Medical Imaging and Graphics, 35(2), 99-104.

[13] Jafari, M. H., Nasr-Esfahani, E., Karimi, N., Soroushmehr, S. R., Samavi, S., & Najarian, K. (2017). Extraction of skin lesions from non-dermoscopic images for surgical excision of melanoma. International journal of computer assisted radiology and surgery, 12, 1021-1030.

[14] Yuan, Y. (2017). Automatic skin lesion segmentation with fully convolutional-deconvolutional networks. arXiv preprint arXiv:1703.05165.

[15] Bi, L., Kim, J., Ahn, E., & Feng, D. (2017). Automatic skin lesion analysis using large-scale dermoscopy images and deep residual networks. arXiv preprint arXiv:1703.04197.

[16] Mishra, R., & Daescu, O. (2017, November). Deep learning for skin lesion segmentation. In 2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM) (pp. 1189-1194). IEEE.

[17] Adegun, A., & Viriri, S. (2019, August). Deep learning model for skin lesion segmentation: Fully convolutional network. In International conference on image analysis and recognition (pp. 232-242). Cham: Springer International Publishing.

[18] Iranpoor, R., Mahboob, A. S., Shahbandegan, S., & Baniasadi, N. (2020, December). Skin lesion segmentation using convolutional neural networks with improved U-Net architecture. In 2020 6th Iranian Conference on Signal Processing and Intelligent Systems (ICSPIS) (pp. 1-5). IEEE.

Declaration of Interests

We, the authors of this research manuscript, declare that we have no financial interest. We have provided written comments to publish the paper in this journal.

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