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Skin Lesion Classification using Optimized Skin Net Algorithm

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ABSTRACT

Skin cancer is one of the much general human diseases realized in all over the world. About five million newer cases of this diseases are realized in the US every year. Early detection and assessment of lesions in the skin are of utmost clinical importance, however, significant issue gets raised whenever there is nil co-ordination between the skin specialist and patient. As a result, a unique deep structure known as Optimized Skin Net is proposed in this work to provide faster screening resolution and help to recently gained physicians in their efforts to make clinical diagnoses of skin-related malignancy. The major motive behind the design and development of Optimized Skin Net is based on two levelled pipelines. Those two levels include where in the lesion segmentation and the lesion classification. The images of the skin diseases have been taken from the publicly available dataset to train and test our deep learning model. Finally, we will be presenting the simulation results along with the outcomes by means of several performance measures like Accuracy, Sensitivity, Specificity, Error rate, False Positive Rate, and ROC.

Keywords : Skin Net cancer, lesions, Optimized Skin Net, segmentation, and classification.

I. INTRODUCTION

Skin cancer is the unmanageable abnormal cells growth in the epidermis (outermost layer of the skin) (Stern) [1]. Asper the statistics revealed by WHO-World Health Organization, the said disease occupies one-third of rest of the cancers, and one in every five persons in US would be identified with skin disease when they reach 70 years of age (Barata C., Celebi, M. E., & Marques) [2]. The three major skin cancer types include the following: SCC- Squamous Cell Carcinoma, BCC- Basal Cell Carcinoma, and melanoma. Out of the three, SCC and BCC are the most general skin cancer forms (Rogers, H. W., Weinstock, M. A., Feldman, S. R., & Coldiron) [3]. These two skin cancer forms could be cured with much ease, while melanoma cannot be cured with much ease and it contributes to increased mortality rates than other skin cancer forms. Over 1.3 lakhs people across the globe were detected with melanoma skin cancer and around 9000 casualties got reported in US according to (Arik, A., Gölcük, M., & Karslıgil, E. M.) [4]. In the years 2020 and 2021, even the developed countries like US were reported to face more casualties because of the melanoma skin cancer (Attique Khan, M., Sharif, M., Akram, T., Kadry, S., & Hsu,) [5].

Globally, the cases of the skin cancers and its subsequent deaths keep on increasing in many continents like Australia, Europe, Asia, etc. (Bennett, H. G., Dahl, L. A., Furness, J., Kemp-Smith, K., Climstein,) [6]

As a solution to these ever-continuing skin cancer cases, the Machine Learning (ML) has been utilized by the researchers across the whole globe. However, the model devised was trained and tested on different types of data at times, which reduces the accuracy rate of predictions made with regards to the skin diseases as per (Quinonero-Candela, J., Sugiyama, M., Schwaighofer, A., & Lawrence) [7]. Furthermore, as the population of the patients change for every unique location, the corresponding attributes realized from those population also borne to get varied. The publicly available datasets are not robust enough when it comes to the patient population in different locations (Thiagarajan, J. J., Rajan, D., & Sattigeri,) [8]. Consequently, the researchers started adopting the Deep Learning methodologies over the ML methodologies owing to its benefits. Despite the benefits served by DL methodologies, there is a stringent need to know regarding whenever the model can give correct results or whenever the model can give wrong results. Therefore, we are going to build an effective system using DL known as Optimized Skin Net algorithm.

Literature Review

(Zhang, J., Xie, Y., Xia, Y., & Shen) [9] introduced an ARL-CNN (i.e., Attention Residual Learning Convolutional Neural Network) framework that consists of a global average pooling layer, a classification layer, and several ARL blocks for the categorization of skin lesions in dermoscopic images. To increase its capacity for discriminative representation, each ARL block works in tandem with unique attention learning processes and residual learning.

(Lopez, A. R., Giro-i-Nieto, X., Burdick, J., & Marques) [10] presented a deep learning-based system for identifying whether a dermoscopic image of a skin lesion is malignant or benign. The proposed approach makes use of the transfer learning concept and is based on the VGG Net convolutional neural network design. The proposed technique surpasses the state of the art by a wide margin on the dataset, obtaining a sensitivity value of 78.66%The approach for the ISIC 2019 Skin Lesion Classification Competition was outlined in (Gessert, N., Nielsen, M., Shaikh, M., Werner, R., & Schlaefer) [11]. Dermoscopic pictures must first be used to categorize skin lesions. Dermoscopic pictures and further patient meta data are then employed. For both challenges, the deep learning-based approach took first place. Using the suggested strategy, the study effort addressed a few issues.

(Yap, J., Yolland, W., & Tschandl) [12] described a strategy for enhancing the accuracy of automated skin lesion identification by combining several imaging modalities with patient metadata. The approach was tested on two tasks such as a five-class classification test which was modelled after a real-world clinical scenario and a binary classification test which compares the proposed work with earlier works.

According to a unique regularize approach, (Albahar) [13] presented an innovative prediction which divides skin lesions into benign and malignant lesions. As a result, this classifier distinguishes both benign and malignant tumors. The suggested approach outperformed other edge-cutting techniques with an average accuracy of 97.4% demonstrating its superiority. Several use cases were used to examine how well CNN performs in terms of AUC-ROC with an integrated innovative regulizer

(Mahbod, A., Schaefer, G., Wang, C., Dorffner, G., Ecker, R., Ellinger) [14] suggested a completely automated computational system for classifying skin lesions that makes use of enhanced deep features from a variety of well-known CNNs and from various levels of abstraction. As deep feature generators, three pre-trained deep models such as Alex Net, VGG16, and ResNet-18 were employed. The training of support vector machine classifiers was performed afterwards using the retrieved features. The outputs of the classifier were combined in final step to provide a classification

A reliable CNN (i.e., Convolutional Neural Network) aggregation into a single framework was suggested by (Harangi) [15]. According to the weighted outcome of the contributing CNNs, the final classification was attained in this case. The paper evaluated various fusion-based aggregation techniques and chose the one that solved the issue most effectively. As each of the implemented fusion procedures exceeds the individual networks in terms of classification accuracy, the experimental findings also demonstrate the value of assembling an ensemble of several neural networks.

(Qin, Z., Liu, Z., Zhu, P., Xue) [16] The suggested approach adapts the discriminator and generator to effectively synthesize high-quality pictures of skin lesions by changing the original generator's noise input and style control structures. For the classification of an image, a transfer learning approach was utilized to build the classifier on a pre-trained deep neural network. In order to improve the performance of classification, the synthetic images of the suggested based on skin lesion style were eventually incorporated to the training set.

According to pre-trained CNNs and transfer learning, (Mahbod, A., Schaefer, G., Wang, C., Ecker, R., & Ellinge) [17] looked at the impact of picture size for the classification of skin lesions. Six distinct sizes, ranging from 224x224 to 450x450, have been cropped or downsized using dermoscopic pictures from the ISIC (i.e., International Skin Imaging Collaboration) skin lesion categorization challenge datasets. Specifically, EfficientNetB0, EfficientNetB1, and SeReNeXt-50 were three well-known CNNs whose classification performance was examined as the outcomes.

(Sae-Lim, W., Wettayaprasit, W., & Aiyarak) [18] introduced a method for classifying skin lesions depending upon Mobile Net which is a low weight deep CNN. Mobile Net was used to classify skin lesion in the study, and a modified version of Mobile Net was also suggested. The study employed a set of multisource dermatoscopic pictures from the HAM (i.e., Human Against Machine) official dataset which consists of 10,000 images for the assessment of the model. To increase the effectiveness of the classifier, data augmentation and data up-sampling techniques were applied in the study. The comparative findings indicated that the modified model had outperformed the standard Mobile Net in terms of various performance measures.

EXISTING METHOD

The existing methodology uses the Machine Filtered Transfer Learning Algorithm to Classify the given skin lesion image as seborrheic keratosis or melanoma. Coming to Transfer Learning will define it as follows. It is a machine learning research subject that focuses on preserving information obtained while addressing one problem and applying it to another but similar challenge. Previous learning is frequently referred to as the source, and subsequent learning as the objective. Essentially, it employs a pre-trained neural network (trained for Task1) to reduce training time (positive transfer learning) in learning Task2. Transfer learning is a prominent mode of learning in modern multistage neural networks known as deep neural networks.

To examine the transfer learning-based skin lesion classification technique, this has separated the proposed MFTL framework into multi-view weighting representation and filtered domain adaption modules. When it comes to multi-view scaling representation, it employs distinct CNN to extract key descriptions for each view of a picture and then classifies each view using distinct classifiers. FDA (Filtered Domain Adaptation) has two datasets: a source dataset and a target dataset. The source dataset is the dataset used to build the model. It will be tested against the specified information. Both the source and target datasets are accessible during training in data augmentation, but labels for the target dataset are not always available. How ever during pre-processing step of unstructured feature acclimation, no classifications are available for the targeted dataset. This means that a model trained on one dataset might not have the ability to learn the same job on a subtly different dataset. The most frequent approaches to the filtered domain adaptation is to take an adversarial approach, in which the encoder and classifier are trained to achieve high classification accuracy on the source dataset first. The discriminator is used to teach the encoder to lose domain discriminability. Using an adversarial loss, the discriminator is taught to categorize the two domains. Because it is hostile to the discriminator, the encoder is trained with the negation of this loss. This is accomplished using gradient reversal, which implies that in backpropagation, the gradients are negated before they reach the encoder. Finally, it employs a source sample distillation approach to pick more useful source samples, which can improve domain adaptability between source and destination domains. The method selects more relevant samples that are within the target domain, according to the notion of Wasserstein distance. It improves the target prediction task even further by using selected source samples.

In this existing methodology the total data set is divided into training data set and testing data set which is in the ratio of 70:30

This paper adopts the accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC) as evaluation criteria in order to evaluate the metrics of MFTL network.

In this, Existing methodology has high error rate, and low sensitivity, and low accuracy and low specificity. So, to improve these metrics moving towards another methodology called Optimized Skin Net Algorithm.

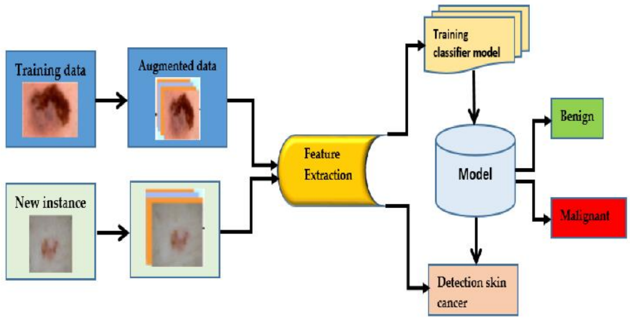

Figure 1: Flow of existing method

II. PROPOSED METHOD

This section discusses the various techniques used in our Optimized Skin Net framework.

Skin Net is a convolutional neural network (CNN) model and a subset of the ANN model. To enhance accuracy, most deep learning algorithms employ many layers of artificial neurons. Such extensive processing, however, necessitates a higher memory and processing footprint from the hardware. Furthermore, the usage of optimizers assisted us in optimizing the learning rate to decrease losses. This took the training data as input and then added 64 neurons to our first dense layer. Following that, a 0.001 kernel-regularizer was applied as an attribute to this thick layer. Eventually, one of the most important activation layer functions, ReLU, was included. Just 32 neurons were extracted in the second phase of the thick layer and connected with 0.002 kernel regularizer. Similar activation layers and first dense layer dropout rates were then introduced here. A 0.001 kernel regularizer was coupled to the dropout rates of a preceding dense layer in the third phase. The ReLU activation layer was then added to this layer, along with minimum dropout rates (0.002). To get a more reliable outcome, the SoftMax activation layer was combined with two output layers, benign and malignant, in the final phase.

This section outlines the approaches utilized in the model for pre-processing. Pre-processing is a critical stage in image processing to generate accurate results. Because there are hairs in some of the images, precise diagnosis may be impaired. will first take the input image and rotate the input image in different angles so that this can estimate the importance of each view. Here this will rotate the input image in 90, -90, and 180 degrees so that this do not miss any detail from the input image. After that this will convert the image to 128*128 pixels and will remove the hair and other unknown data from the input image that is not needed for us by using DHR (Digital Hair Removal) method. After this step the input image was given to Google Net for testing and training of images.

CNN is one of the kinds of Neural Network that is often used for image detection and classification. It includes supervised learning, which consists of biases or weights in filters or neurons. Each filter takes some inputs and performs convolution to the gathered input. Convolutional, pooling, Rectified Linear Unit (ReLU), and Fully Connected layers define the CNN classifier.

Convolutional layer:

This layer takes the image that was applied as input and extracts its features. The output image from this layer is provided as an input to the following convolutional layer after the neurons have convolved the input image to create a feature map.

Pooling layer:

Through implementing this layer, the extent of the feature chart can be drastically decreased preserving the necessary information. In most scenarios, this layer is placed between the two convolutional layers.

ReLu layer:

The non-linear procedure ReLu replaces all negative values in the feature map with zero. It is an element-by-element operation.

FLC denotes that each filter in the previous layer is linked to each filter in the following layer. This is used to categorize the input image into various categories based upon the training dataset.

It has four phases:

1. Model construction
2. Model training
3. Model testing
4. Model evaluation

Machine learning algorithms are employed for developing models. It was Convolution Neural Networks in this project's scenario. Model training begins after model construction. The model is trained here using training data and predicted output from this data. Model testing can be done after the model is fully trained. Another set of data is loaded during this phase. Because the model has never encountered this data set before, its true accuracy will be validated. After the model training is finished, the stored model can be used in real life. This step is known as model evaluation.

Google Net is a convolutional neural network that is 22 layers deep. The Google Net-trained network divides images into 1000 objects and variety of skin lesions. Google engineers created the Deep Learning model known as Google Net, also referred to as Inception Net. The data is then divided into training and testing parts. The training part uses 75% of the data, while the remaining 25% is used in the testing phase. Among these training data, 1000 pictures are chosen at random from the benign class and 800 images are chosen from the malignant class. Similarly, 700 images are chosen at random from each benign and malignant category. Then SkinNet-16, a deep learning classifier, is used to classify the given input image as Seborrheic Keratosis (or) melanoma.

Evaluation metrics

This study uses accuracy, sensitivity, specificity, and error rate as evaluation metrics to quantify the performance of our proposed Optimized Skin Net algorithm.

These metrics are calculated by

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+TN+FP} \quad (1)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (3)$$

Where TP, FN, TN, and FP denote the number of true positives, false negatives, true negatives, and false positives separately.

Table 1: Seborrheic Keratosis classification metrics

Methods	**Accuracy (%)**	**Sensitivity (%)**	**Specificity**
MFTL	86.2	62.4	91.9
Optimized Skin Net algorithm	97.0	96.2	97.8

Table 2: Melanoma classification metrics

Methods	**Accuracy (%)**	**Sensitivity (%)**	**Specificity**
MFTL	88	88.9	87.8
Optimized Skin Net algorithm	97.0	96.2	97.8

III. SIMULATION RESULTS

This section provides with the simulation results of the proposed Optimized Skin Network Algorithm.

Input Image:

As the optimized Skin Net is being trained for more than 500 images now this will be taking one random image as an input so that it can classify the given input image as either Seborrheic Keratosis or Melanoma. Now this will be taking the case of Seborrheic Keratosis which is as follows.

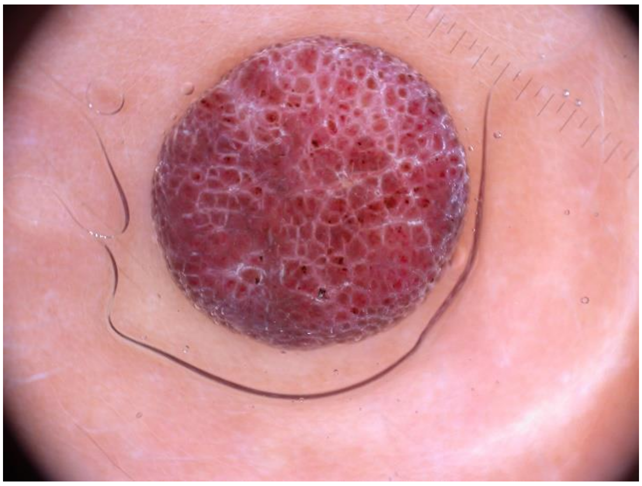

Figure 2: Input image of Seborrheic Keratosis

Input Image of Seborrheic Keratosis is taken in different Views:

This has taken an input image in different views so that this do not miss any important detail of an image

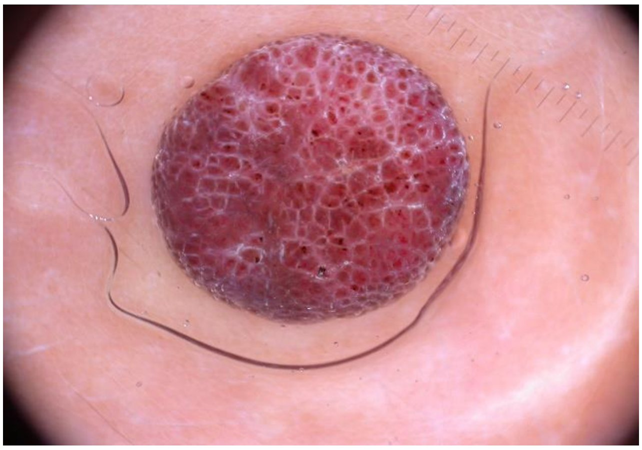

Figure 3: Input image of view-1

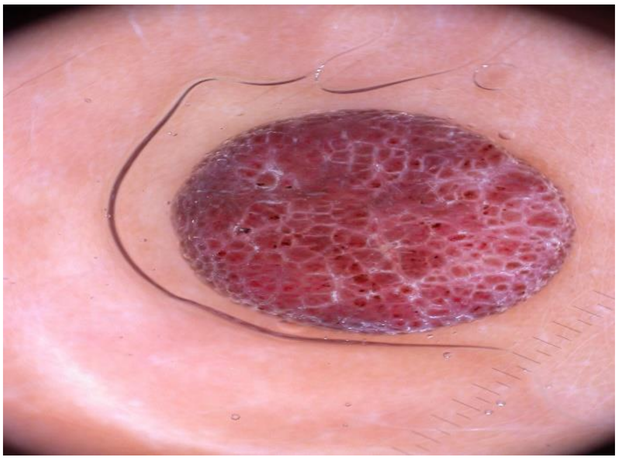

Figure 4: Input image rotated by 90°

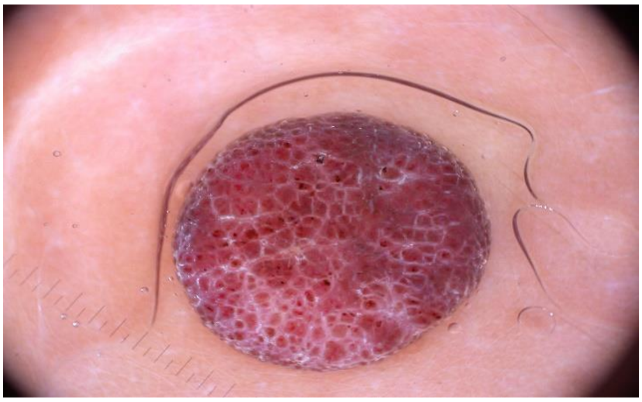

Figure 5: Input image rotated by -90°

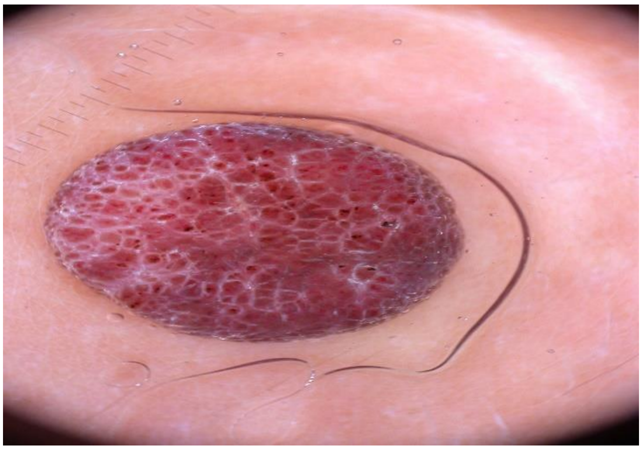

Figure 6: Input image rotated by 180°

Sample Training Images:

It has taken a random input image from this dataset shown below.

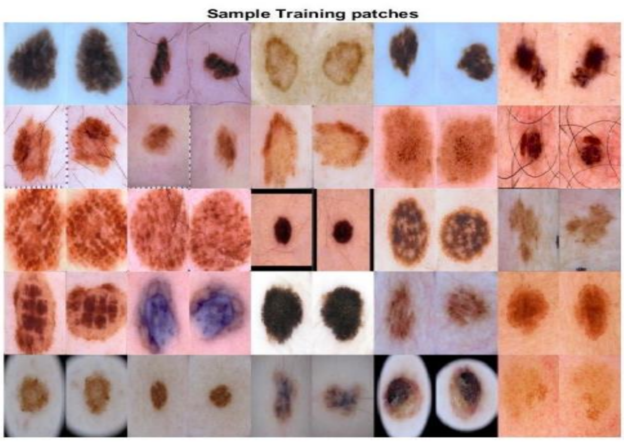

Figure 7: Sample Training Images

Output:

Predicted class is Seborrheic Keratosis

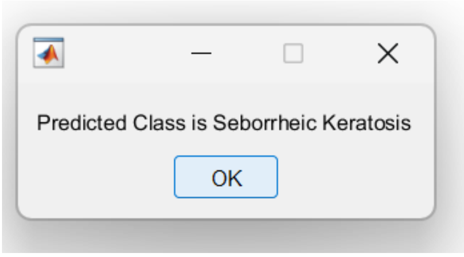

Figure 8: popup message showing predicted class

Confusion Matrix:

An analysis of a machine learning model's performance on a set of test data is summarized by a confusion matrix. It is frequently used to assess how well categorization models work. These models try to predict a category label for each input event. The matrix shows how many true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) the model generated using the test data.

Table 3: Confusion matrix of Seborrheic Keratosis

Label	**Positive**	**Negative**
Positive	102	4
Negative	2	92

ROC (Receiver Operating Characteristic) Curve of Seborrheic Keratosis:

It is a measure of overall performance for classification problems at different threshold levels. It indicates how well a model can differentiate between classes.

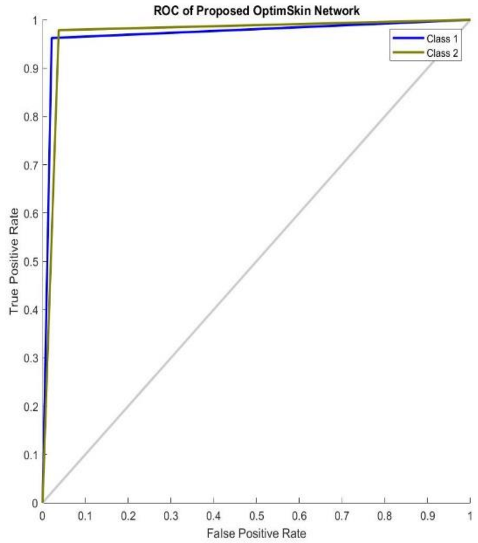

Figure 9: ROC plot of Seborrheic Keratosis here class 1 denotes ROC curve of MFTL algorithm and class 2 the denotes ROC curve of Skin Net algorithm

Comparison of Evaluation Metrics of Existing and

Proposed Method:

The comparison of evaluation metrics for existing and proposed techniques can be seen in the figure below. Proposed method evaluation measures perform better than those for existing methodology in terms of accuracy, error rate, specificity, and sensitivity.

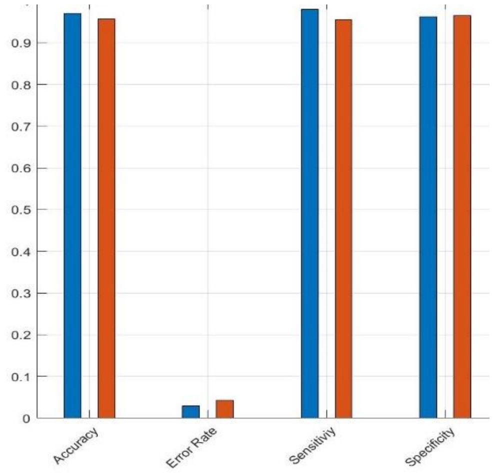

Figure 10 Comparison of Evaluation Metrics of Existing (shown in red color in graph) and Proposed Method (shown in blue color in graph)

Simulation Results of Melanoma:

Input Image:

As the optimized Skin Net is being trained for more than 500 images now this will be taking one random image as an input so that it can classify the given input image as either Seborrheic Keratosis or Melanoma. Now this will be taking the case of Melanoma which is as follows.

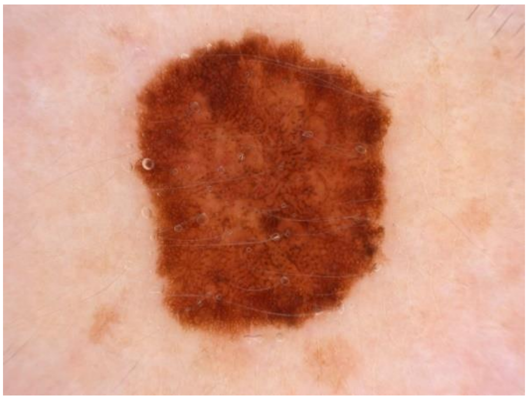

Figure 11: Input image of melanoma

Input Image in different Views: This has taken an input image in different views so that this do not miss any important detail of an image

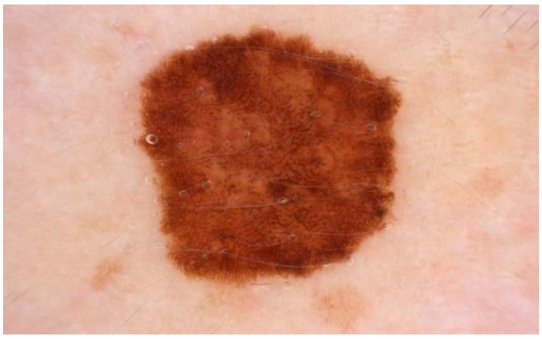

Figure 12: Input image of view-1

Figure 13: Input image rotated by 90°

Figure 14: Input image rotated by -90°

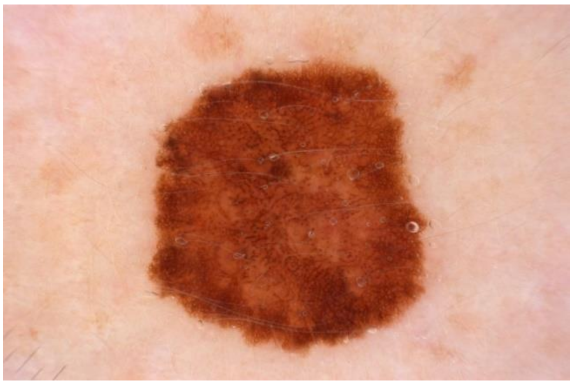

Figure 15: Input image rotated by 180°

Sample Training Images:

It has taken a random input image from this dataset shown below

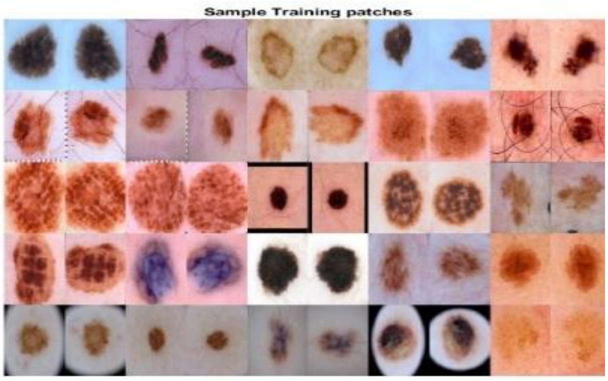

Figure 16: Sample Training Images

Output: Predicted class is Melanoma

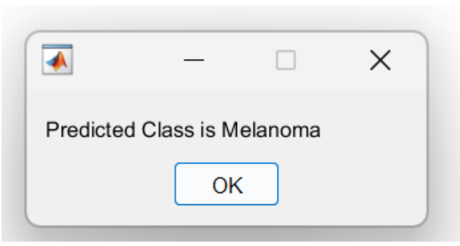

Figure 17: popup message showing predicted class

Confusion Matrix:

An analysis of a machine learning model's performance on a set of test data is summarized by a confusion matrix. It is frequently used to assess how well categorization models work. These models try to predict a category label for each input event. The matrix shows how many true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) the model generated using the test data.

Table 3: Confusion matrix of melanoma

Label	**Positive**	**Negative**
Positive	102	4
Negative	2	92

ROC (Receiver Operating Characteristic) Curve of Melanoma:

It is a measure of overall performance for classification problems at different threshold levels. It indicates how well a model can differentiate between classes.

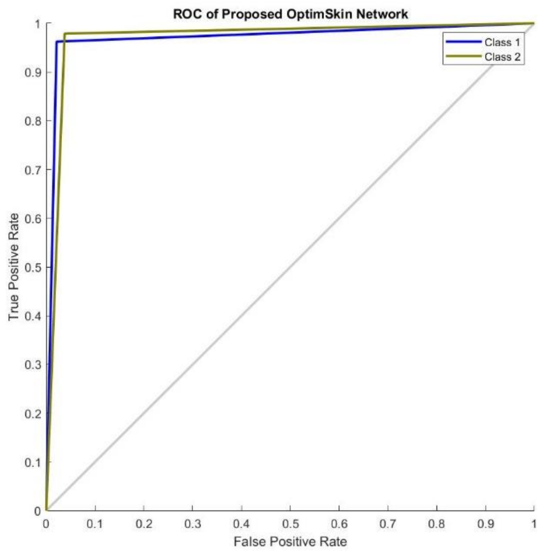

Figure 18: ROC plot of Seborrheic Keratosis here class 1 denotes ROC curve of MFTL algorithm and class 2 the denotes ROC curve of Skin Net algorithm

Comparison of Evaluation Metrics of Existing and Proposed Method:

The comparison of evaluation metrics for existing and proposed techniques can be seen in the figure below. Proposed method evaluation measures perform better than those for existing methodology in terms of accuracy, error rate, specificity, and sensitivity.

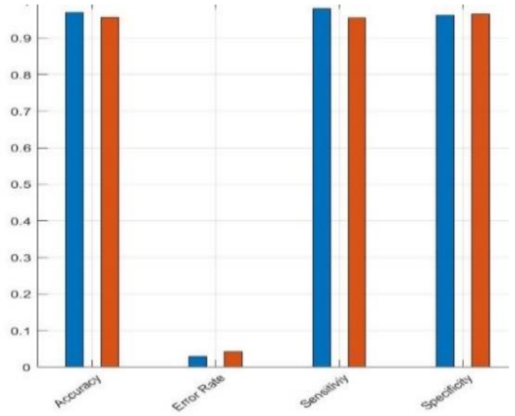

Figure 19: Comparison of Evaluation Metrics of Existing (shown in red color in graph) and Proposed Method (shown in blue color in graph)

IV. CONCLUSION AND FUTURE WORK

In this research work, a novel deep structure named Optimized Skin Net was proposed as a redressal for classifying the skin lesions into certain categories like Melanoma and Seborrheic Keratosis after subsequent segmentation. The said Optimized Skin Net was able to classify the given skin lesion images in a much quicker succession. The effectiveness of our devised schema known as Optimized Skin Net was validated in terms of several performance measures, namely, Accuracy, Sensitivity, Specificity, Error rate, False Positive Rate, and ROC.

As a future work, this paper would like to experiment with more diverse datasets dealing with diverse diseases in addition to the skin cancers/ lesions to make our research classification task more robust than the current version.

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