

**ENHANCED MULTI-CLASS SKIN CANCER CLASSIFICATION THROUGH SCD-NET ON DERMOSCOPY DATA****Dr. A. Kalaivani**

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ABSTRACT—

The global incidence of skin cancer, a severe and potentially fatal malignant skin disease, has been steadily increasing in recent years. Early and accurate diagnosis is crucial for effective treatment and improved patient outcomes. However, communication barriers between patients and dermatologists often result in a knowledge gap regarding the symptoms and stages of various skin conditions. To address this issue, this study introduces a novel deep learning-based skin disease classification model utilizing advanced machine learning techniques. The proposed model undergoes several preprocessing steps, such as noise reduction, hair removal, and image resizing, to enhance dermoscopic image quality. Automated diagnosis of skin malignancies from dermoscopic images remains a complex and challenging task, especially for supporting medical decision-making. In the segmentation phase, the LeNet-5 architecture is employed to identify lesion areas and accurately segment skin abnormalities. Subsequently, the LeNet-5 classifier categorizes the segmented lesions as either benign (non-melanoma) or malignant (melanoma).

Furthermore, the Eigenvector Decomposition Analysis (EDA) technique is applied to extract discriminative features such as texture, shape, and color, enabling more precise lesion classification. To extend the model's diagnostic capability, this research proposes a multi-classification framework named Skin Cancer Diagnosis Network (SCD-Net), designed to identify multiple malignant skin conditions using dermoscopic images. Experimental evaluation using the ISIC 2019 dataset demonstrates the superior performance of the proposed model, achieving higher accuracy, precision, recall, and F1-score compared to existing classification methods. The robust classification performance of SCD-Net can assist dermatologists and patients in the early and reliable detection of skin diseases, facilitating timely clinical intervention and improved treatment outcomes.

Keywords—Deep learning, Feature extraction, Skin cancer, Segmentation**I. INTRODUCTION**

Human skin serves as a vital barrier between the body and its external environment. It is the largest organ of the human body, composed primarily of water, proteins, fats, and minerals. Any disorder that affects this protective organ is classified as a skin disease. Such conditions can be highly contagious and may lead to serious health complications. In 2018 alone, skin cancer accounted for 2,794 deaths in Bangladesh, while globally, it affected more than 14 million individuals and caused approximately 9.6 million fatalities [1]. Skin diseases may arise due to various factors, including bacterial, viral, fungal, or allergic infections, as well as genetic predispositions, and are often manifested through changes in skin texture or color [2]. These disorders primarily affect the epidermis—the outermost layer of the skin—resulting in both physical discomfort and psychological distress [3]

Skin cancer is the result of unchecked, aberrant skin cell growth, which also results in malignant tumours [4]. A DNA mutation causes skin cancer, and exposure to UV radiation damages these cells. This mutation prevents skin cells from proliferating normally [5]. According to the World Health Organisation, skin cancer accounts for thirty percent of all cancer cases worldwide [6]. The public health issue of skin cancer affects people all around the world [7,8].



Actinic Keratosis (AK), Basal Cell Carcinoma (BCC), Benign Keratosis (BKL), Dermatofibroma (DF), Melanoma (MEL), Melanocytic Nevus (NV), Squamous Cell Carcinoma (SCC), and Vascular Lesion (VASC) are among the various forms of skin lesions that can be distinguished [9]. Lesions can be painful or painless, and some have transient or permanent symptoms. There is also variation in their intensity. Although melanoma is the deadliest form of skin cancer, ninety-five percentage of cases can be successfully treated with early identification [10].

Among the various skin lesions, melanoma is a well-known type of skin cancer and is frequently the most dangerous [11]. One of the skin cancers that spreads the fastest is melanoma [12]. Accurate skin lesion classification by computer-aided automatic approaches is beneficial for human life preservation [13].

Skin illnesses can be accurately classified with the aid of an automated computer-aided system [14]. Patients and dermatologists are at odds because the general public is largely ignorant about the various kinds, signs, and phases of skin diseases. Although early detection is essential for effective treatment, precisely diagnosing skin illnesses can be expensive and difficult. More rapidly and correctly identifying the many forms of skin diseases is now achievable thanks to autonomous computer-aided systems based on machine learning techniques [15]. Over the past three decades, a large number of studies have been undertaken in the important field of skin disease classification study. Though a lot of study has been done on the subject, detection and classification techniques can yet be improved. Prior research has mostly concentrated on individual diseases and has not been able to adequately identify numerous classifications. Because many skin illnesses exhibit similar behaviours, classifying them can be difficult.

Thus, a novel automatic categorization model for various skin diseases is introduced in this study. Some of the primary contributions of this technique are:

- Utilizing preprocessing techniques like image resizing, hair removal, and noise removal to improve skin image quality.
- Employing the LeNet-5 method to identify and segment lesion regions in skin images without losing any information.
- Extracting colour and texture features using the Eigenvector Decomposition Analysis (EDA) approach.
- Developing the Skin Cancer Diagnosis Network (SCD-Net) model trained on colour and texture features for accurate classification of skin diseases.

The rest of a paper is structured as follows: A survey of the literature is covered in Section II. The proposed paradigm is explained in Section III, and its effectiveness is shown in Section IV. The findings of the research and suggestions for improvements are provided in Section V.

II. LITERATURE SURVEY

Articles that discuss the methods for automatic melanoma identification using deep learning algorithms for dermoscopic images are common and could help pave the way for improved medical research.

A multi-class multi-level classification system was constructed by Hameed et al. [16] to identify different skin conditions. Pre-processing noise reduction, a hybrid method for Region of Interest (ROI) extraction, colour and texture feature extraction, and picture classification are all included. Deep learning directly from images was achieved through the use of transfer learning. The dataset's inconsistent nature as a result of data collection from multiple sources was a drawback, though. Using image processing, Sinthura



et al. [17] created a model for diagnosing skin diseases. Using Otsu's approach, they divided the illness part into segments and extracted features from the Grey Level Co-occurrence Matrix (GLCM), such as area, perimeter, mean, and entropy. Next, four illness types were classified using the Support Vector Machine (SVM) classifier: rosacea, melanoma, psoriasis, and acne. It was tested, while on a little dataset with few features.

Khan et al. (2021) [18] developed a brand-new deep learning model for segmentation and classification. DCNN is used for skin lesion classification, while optimised colour feature (OCF) is used for skin lesion segmentation. In this study, a hybrid method is proposed to enhance lesion contrast and reduce artefacts. After that, colour segmentation is done using the OCF. The OCF methodology is enhanced utilising an established saliency approach, and the strategy is fused together using a novel pixel-based method. In order to extract the deep features and fuse them with the OCF strategy, a DCNN-9 model is created utilising a novel parallel fusion technique (Saeed & Zeebaree, 2021) [19].

Femil & Jaya's (2023) [20] systematic image processing approach was applied for the accurate diagnosis of skin cancer. Noise is eliminated from dermoscopy images of skin lesions using the Gabor filter. The pre-processed dermoscopy image is then divided into distinct sections using a cascaded fuzzy c-means (FCM) algorithm. The Gabor response co-occurrence matrix (GRCM) is an efficient method for extracting the melanoma parameters. The probabilistic neural network (PNN) classifier is used to effectively categorize the phases of skin lesions in order to significantly detect the features.

Hosny, Kassem, and Foad (2020) [21] offered a revolutionary CNN approach. There are three main stages to the proposed plan. The first pre-processing phase is segmenting the ROI for input pictures. Translation and rotation adjustments improve the segmented ROI images. As a last stage, multiple DCNN configurations are used, such as Alex-net, ResNet101, and GoogleNet.

Jagdish et al. [22] used image processing methods to develop a model for the diagnosis of skin diseases. They applied SVM and K-Nearest Neighbour (KNN) classification methods with wavelet analysis and fuzzy clustering on a small sample of photos. It correctly diagnosed the kind of skin condition. It was tested, therefore, only on a small sample of pictures from the squamous and basal disease classes. Naeem et al. [23] used SVMs and image processing methods to create a skin cancer prediction model. They used the GLCM approach in conjunction with image improvement and noise reduction approaches to extract characteristics from the images. The images were then classified as either malignant or non-cancerous by the classifier. Nevertheless, the limited dataset constrained the model's capacity to be applied broadly.

Hatem [24] created a system for identifying and categorizing skin lesions using the KNN classifier. It was, nevertheless, evaluated on benign and normal class photos. Maduranga et al. [25] classified skin disorders using the HAM10000 dataset using MobileNet with transfer learning. It could have been more accurate, though. The Optimal Probability-based Deep Neural Network (OP-DNN) was first presented by Jain et al. [26] as a tool for diagnosing skin diseases. They trained the OP-DNN, extracted features, and preprocessed the images. Nevertheless, the sensitivity and classification accuracy were inadequate.

III. PROPOSED METHODOLOGY

This section explains the proposed skin diseases classification model in detail. A general block diagram of this study is depicted in Figure 1. The process consists of four main steps: image preprocessing, lesion segmentation, feature extraction, and classification.

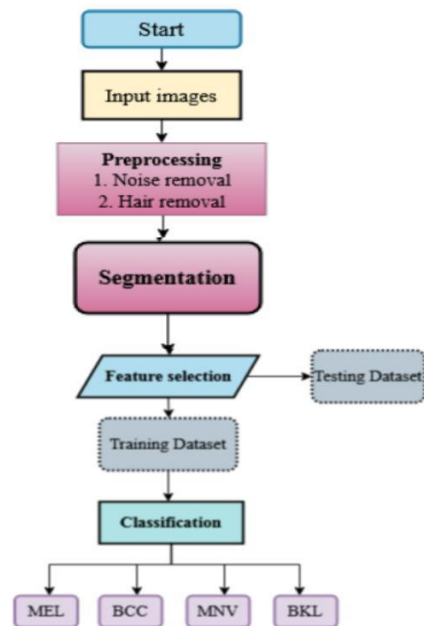


Figure 1. General Block Diagram of the Proposed Study

3.1 Dataset Description

In this study, the following two well-known datasets are considered:

- ISIC 2019 Challenge Dataset: The ISIC is an International Collection of Dermoscopic Images. In this field of study, the most often deployed dataset was the ISIC 2019. The dataset can be viewed at <https://challenge.isic-archive.com/data#2016>. The ISIC 2019 dataset is one of the hardest to identify because of an imbalanced number of images among the eight groupings. The collection comprises 25,331 dermoscopic images with various skin cancer classes. The collection includes 2,624 images of benign keratosis, 3,323 images of basal cell carcinoma, 12,875 images of melanocytic nevi, and 4,522 images of melanoma. The dataset's remaining class images are not considered. The dataset is split into training, testing, and validation sets in the following ratios: 70%:20%:10.
- This study focused on the training dataset of the ISIC 2019 challenge, which includes 25331 dermoscopic pictures of four different classes: BCC, BKL, MEL, NV.
- The proposed Skin Cancer Diagnosis Network (SCD-Net) model is trained using dermoscopic images of benign keratosis (BKL), melanoma (MEL), melanocytic nevi (NV), and basal cell carcinoma (BCC) from the ISIC 2019 dataset. The proposed framework is trained, tested, and



validated using images with a 70:20:10 ratio. Table 1 displays an overview of the dataset. Figure 2 presents a representation of images from the ISIC 2019 datasets.

Table 1. Distribution of Skin Images in Dataset

Classes	Division of Dataset			
	Training set	Testing set	Validation set	Total
Basal Cell Carcinomam (BCC)	2,327	664	332	3,323
Benign Keratosis (BK)	1,837	524	263	2,624
Melanoma (MEL)	3,166	904	452	4,522
Melanocytic Nevi (NV)	9,013	2,575	1,287	12,875
Total images	17,731	5,066	2,533	25,331

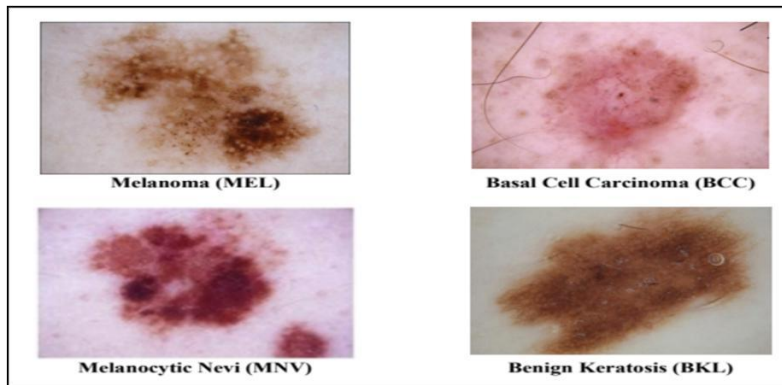


Figure 2. Sample images of multiple skin cancer classification

3.2 Preprocessing

Image preprocessing is transforming an image into a format that is more suited for its intended application. Unwanted hair, noise, and distortion are common in skin photos, which can negatively impact an image processing system's performance. Preprocessing skin images increases image quality, decreases complexity, and increases accuracy, all of which are critical for optimizing the performance of skin disease detection systems. First, the Rank-Order Filter and a Laplacian of Gaussian based methods are used to pre-process the input images. Hair can greatly or partially cover certain types of melanoma, so it is removed before using the dermoscopic input images as input for segmentation. The image is converted to grayscale and then sharpened using a Laplace operator-based filter. Subtracting the filtered image from the original image is the next step. Unwanted image noise can be eliminated by applying a median filter. The median filter works quite well in maintaining the edges of an image. A median filter is used to eliminate noise from the images after the hair has been cut off.

The dermoscopy images in the dataset have a resolution of 450 x 600 pixels. To standardize the image resolution with the model input, we decreased it to 224×224 pixels. Additionally, the data normalization technique was used to guarantee proper training of the proposed method. Next, we generated the datasets

needed for the training of the Skin Cancer Diagnosis Network (SCD-Net). Figure. 3 illustrates the effectiveness of the noise and hair removal processes during the pre-processing stage.

Laplacian of Gaussian filtering

Laplacian of Gaussian (LoG) filtering is a technique used in image processing and computer vision to detect edges and fine details in an image. It involves two main steps: Laplacian of Gaussian (LoG) filtering involves first smoothing the image using a Gaussian filter, which helps to reduce noise and minor variations in the image, making the subsequent edge detection more robust. After smoothing, the Laplacian operator is applied to the smoothed image; this operator is a second-order derivative filter that highlights regions of rapid intensity change, corresponding to edges. The combined process is effective in edge detection because the Gaussian smoothing step reduces noise, while the Laplacian step highlights the edges. The result is a filtered image where edges are marked by zero-crossings or areas of high intensity change [27].



Figure 3. Noise and hair elimination in pre-processing

Mathematically, the LoG filter is represented by the convolution of the image $I(x,y)$ with a kernel that combines the Gaussian and Laplacian functions:

$$\text{LoG}(x,y) = \nabla^2(G(x,y) * I(x,y)) \quad (1)$$

where $G(x,y)$ is the Gaussian function and ∇^2 is the Laplacian operator.

$$\text{LoG}(x,y) = (\nabla^2 G(x,y)) * I(x,y) \quad (2)$$

where $\nabla^2 G(x,y)$ is the Laplacian of the Gaussian function. This approach is computationally efficient because it simplifies to applying a single convolution with a precomputed kernel.

3.2 Segmentation

The technique of splitting an image into distinct regions according to characteristics including texture, contrast, brightness, color, and grey level is known as image segmentation. This method is crucial for correctly assessing photographs, especially in microscopic images where it can be difficult to tell the difference between healthy skin and lesions because of differences in size, shape, and color.

Precise segmentation is essential because it affects the precision of procedures that come after. The segmentation in this study is done using the LeNet-5 technique. The LeNet-5 method is used when the colors in an image's backdrop and foreground are particularly similar. due to the ineffectiveness of the



other approach's performance. Using this sorting network, superficial skin tumours that are successful are divided into groups. Different extra-convolutional neural networks types may be used for division based on the objectives of each application. Skin cancer has been divided using an already-trained LeNet-5 network. According to Fan Y et al. (2020) [28].

LeNet-5 consists of seven layers: an output layer, two pooling levels, an input layer, one fully connected layer, and two convolutional layers. Table 2. displays the LeNet-5 unique architecture. The same amount of filtering is used to obtain the same final characteristic dimensions. The data sample becomes even off by the convergence at a rate of two passes per layer.

Cluster standardization takes place both prior to and following every convolution, as well as prior to the ReLU being initiated. Although the final and original sizes can be swapped out, a unique method is used. A projector technique using 1x1 convergence is used whenever the dimensions are increased to match the size. A portion of the epidermal disease region is sent for categorization and RPN systems by the final convolutional step.

The LeNet-5 division system uses only the forty-nine convolutional layers; it does not employ the whole linked and average pooled levels. Rather than requiring the final category, the RPN and categorization network only need the network to segment.

Nine boxes anchored in the sizes of 128; 256; and 512 will usually be used in the following percentages: 1:1, 1:2, and 2:1. RPN predicts the likelihood of objects or surroundings existing in a supporting box. The required object proposals are sent to the following step as a group of filter anchor points.

Table 2. Lenet-5 Segmentation Network

Layers	Name of the Layers	Input size	Output size	Pooled area	Convolution Kernel size	Step size
input	Input layer	32*32	28*28	—	5*5	1
Layer1	Convolution layers	6*28*28	6*14*14	2*2	-	2
Layer2	Pooled layers	16*14*14	16*10*10	-	5*5	1
Layer3	Convolution layers	16*10*10	16*5*5	2*2	-	2
Layer4	Pooled layers	16*5*5	120*1*1	-	5*5	1
Layer5	Fully connected layer	1*120	1*84	-	-	-
Layer6	Fully connected layer	1*84	1*7	-	-	-
output	output layer	1*7	—	-	-	-

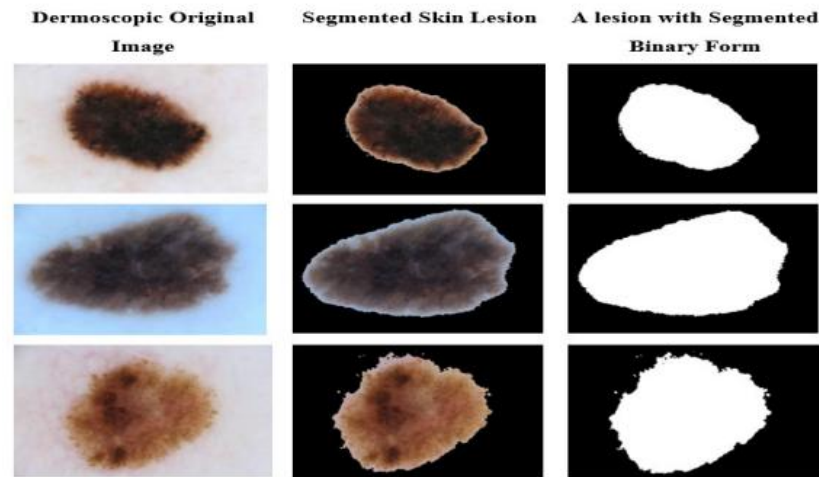


Figure 4. Assessment of Instance Segmentation Using the LeNet-5 Approach

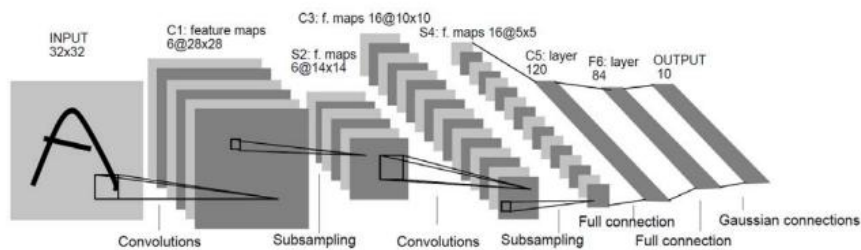


Figure 5. Architecture of LeNet 5 for Skin Image Segmentation

The skin disease region is correctly divided by the LeNet-5 method. Example methods for segmenting photographs of skin lesions are shown in Figure 4. Using the LeNet-5 segmentation algorithm, it presents the segmented skin tumour region numerically as well as displays the segmented tumour region using dermoscopic images.

3.3 Feature Extraction

In order to analyse the interactions between objects, feature extraction is essential. To transform images into forms that are useful for tasks like classification and prediction, image algorithms need to perform feature extraction. Although dermoscopic images have many features, not all of them are important for classifying skin diseases. Accurate categorization depends on selecting the appropriate features for extraction. Effective identification of the type of skin illness can be achieved by extracting color and texture information from segmented lesion images. The Eigenvector Decomposition Analysis (EDA) approach is used in this work to extract characteristics.

After pre-processing, techniques for characteristic extraction have been used to extract the attributes that will be important for picture features. To enhance melanoma prediction, dermoscopic images must serve as the basis for material, color, and design choices. In this phase, Eigenvector Decomposition Analysis (EDA) was used to extract the attributes. Getting features is a crucial stage in the process of creating a design.

The goal of the mathematical technique known as Eigenvector Decomposition Analysis (EDA), [29] which uses an analysis of principal components, is to minimize the size of the database. Symmetric linear conversion is the process of transforming data using a different coordinate system. With the aid of line combinations, the natural traits unveil new characteristics. The characteristics that are most volatile are appropriate for dispatching.



The method of Eigenvector Decomposition Analysis yields noteworthy outcomes and efficiently recovers the characteristics of benign or malignant dermoscopic images. Eigenvector Decomposition Analysis's primary benefit over traditional index-generating techniques is that it does not assign arbitrary or biased values to particular qualities. Weights in principal component analysis are assigned based on the results of a uniform economic evaluation of a few chosen indicators. During the feature extraction phase, all the colour and texture features of the skin images are obtained, which are then fed to the Skin Cancer Diagnosis Network (SCD-Net) classifier.

3.4 Classification

The multi-class classification technique is employed in the proposed Skin Cancer Diagnosis Network (SCD-Net) model for efficient image categorization based on the chosen attributes. SqueezeNet, a deep learning-based model, is used for the multi-class skin cancer categorization. The SqueezeNet convolutional network is employed during optimization. An input used in testing is called a test set. The SqueezeNet neural network handles the classification training and optimization phases. A more straightforward and efficient CNN model is produced by compressing and enlarging the fire module layers. This most efficient network model determines the infection classes' classification performance.

The SqueezeNet architecture consists of fifteen layers: eight fire layers, three max-pooling layers, two convolution layers, one SoftMax output layer, and one global average pooling layer. The stride size is indicated by s , the feature map length is represented by l , and the filter's receptive field size is shown by $K \times K$ notation. The RGB channels and 227×227 image size are the features of the input to the network. The input images are normalized and given the maximum amount of pooling via convolution. The convolution layer concatenates tiny regions and weights in the input volumes using 3×3 kernels.

The final portion of each convolution layer's parameter is that it performs an element-wise activation function. Fire is used in the convolution layers of SqueezeNet, which consists of squeezing and expansion stages. For the fire, there is an equal input and output tensor scale. The squeeze phase employs the 1×1 size filter for classification, whereas the expansion phase uses the 3×3 and 1×1 size filter. The $H \times W \times C$ input tensor is first transmitted by the squeeze.

Throughout the extension and squeezing procedures, the ReLu units are applied. The expansion and squeezing actions compress and extend the depth while maintaining the same size of the feature. The expansion outputs are arranged in the input tensor's depth dimension using the concatenate action.

A weighted mixture of many tensor feature maps is established using the squeeze outputs. A down sampling operation in the network carries out a down sampling operation in the spatial dimensions. In order to create a single value from the class maps with features, the network employs an average global pool. The SoftMax activation function is used to construct multi-class probability distributions at the network's output.

The SoftMax classifier is configured at the output layer of Skin Cancer Diagnosis Network (SCD-Net) model. Their scores are then fused to classify the classes of skin diseases. Table 3 presents the hyperparameters used for constructing the Skin Cancer Diagnosis Network (SCD-Net) classifier.

IV. EXPERIMENTAL RESULTS

This section evaluates the SCD-Net model's performance against other models that are currently in use,



including Inceptionv3 and StyleGANs [32], StyleGAN and DenseNet201 [31], and Inceptionv3 [30]. The skin images datasets covered in Section 3.1 were used to evaluate each model, which was implemented using Python code to provide the experimental findings. The trials are carried out on a Windows 10 64-bit machine equipped with an Intel® Core TM i5-4210 Processor CPU @ 3GHz, 4 GB of RAM, and a one TB HDD. The following assessment metrics are employed to determine the performance improvement:

- Accuracy: It is the proportion of exact prediction over the total data analyzed.

$$Accuracy = \frac{True\ Positive\ (TP) + True\ Negative\ (TN)}{TP + TN + False\ Positive\ (FP) + False\ Negative\ (FN)} \quad (3)$$

In Eq. (3), TP is the number of positive labels correctly classified as positive, TN is the number of negative labels correctly classified as negative, FP is the number of positive labels classified as negative, and FN is the number of negative labels classified as positive.

- Precision: It determines the correctly predicted labels at TP and FP rates.

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

- Recall: It is the proportion of labels, which are correctly predicted at TP and FN rates.

$$Recall = \frac{TP}{TP + FN} \quad (5)$$

- F1-score (F1): It is the harmonic mean of precision and recall.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (6)$$

The presented SCD-Net model classifies various skin cancers using dermoscopic pictures. Using an optimisation process called "stochastic gradient descent" (SGD), the hyper-parameters of the suggested model are adjusted in order to enhance the performance outcomes. The SGD method optimises the number of epochs, batch size, and learning rate. The suggested SCD-Net training procedure is finished in 50 epochs. The SGD optimizer sets the initial learning rate of the proposed Skin Cancer Diagnosis Network (SCD-Net) at 0.05. The momentum value is adjusted by the algorithm to be 0.8. To prevent overfitting, the learning rate was lowered by 0.1 after 10 epochs. The recall, F1-score, precision, accuracy, and confusion matrix are computed for each class label in order to determine the suggested SCD-Net model's performance outcomes.

Table 3. presents the overall classification performance for existing and proposed classifier models using the ISIC 2019 Challenge dataset.

Table 3. Performance Metrics of Proposed and Existing Models on Skin Image Datasets

Dataset	Models	Precision	Recall	F1-score	Accuracy
		(%)			
ISIC 2019 Challenge	Inceptionv3	84.00	83.00	84.00	92.83
	StyleGAN and DenseNet201	91.3	89.32	91.43	92.5

	Inceptionv3 and StyleGANs	86.15	86.43	86.79	86.85
	SCD-Net	88	98.3	97.23	97.5

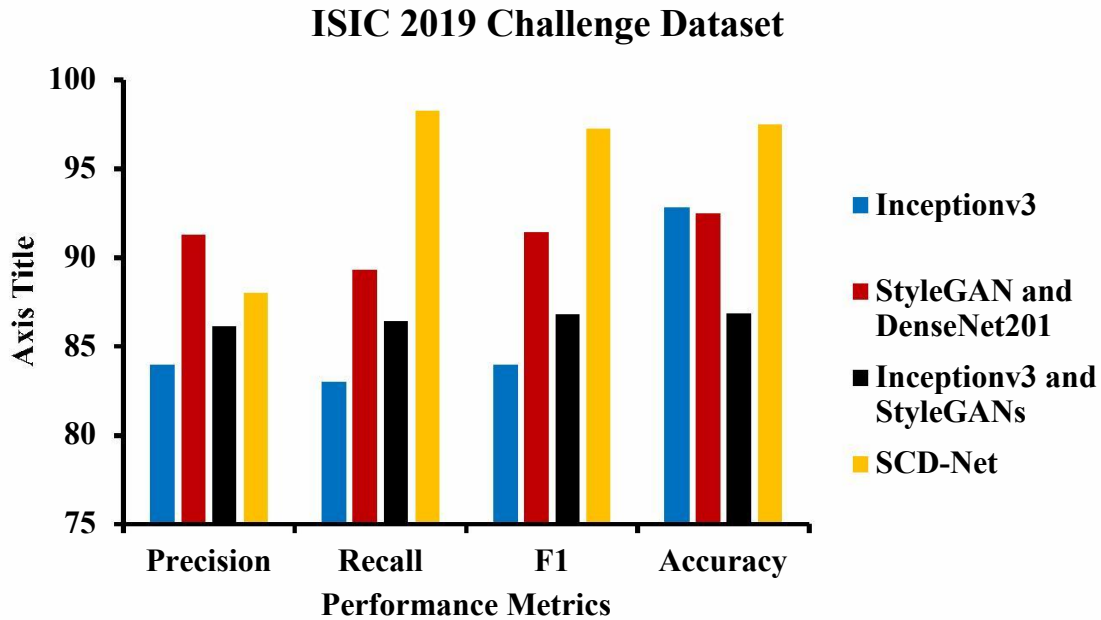


Figure 6 . Comparison of Different Skin Disease Classification Models on ISIC 2019 Challenge Dataset

V. CONCLUSION

This study introduces a new classifier, the SCD-Net model, for precisely classifying multiple skin diseases. It incorporates preprocessing, segmentation, feature extraction followed by the SCD-Net classifier for skin diseases classification. The performance of the DDBN model was evaluated on the ISIC 2019 Challenge, showing superior results compared to traditional classification methods like Inceptionv3 and StyleGANs, StyleGAN and DenseNet201, Inceptionv3. On the ISIC 2019 dataset, the SCD-Net achieved an accuracy of 97.5%, surpassing Inceptionv3 (92.83%), StyleGAN and DenseNet201 (92.5%), and Inceptionv3 and StyleGANs (86.85%). This SCD-Net model can assist dermatologists and patients in the early and accurate detection skin diseases for prompt intervention and treatment. Future research could explore incorporating additional clinical data and expanding the model to classify a wider range of skin conditions.

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