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A Scheme for Effective Skin Disease Detection using Optimized Region Growing Segmentation and Autoencoder based Classification

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Abstract

Detecting skin disorders just through visual inspection is difficult due to the complicated and overlapping nature of sick lesions, background skin textures, skin hair, low illumination, etc. Computer Vision and Machine Learning are playing a great role in identifying the correct type of diseased lesion. However, in the presence of the aforementioned artefacts, current computational approaches are equally limited in their ability to detect complicated lesion structures. We provide a novel detection framework to enhance skin disease diagnosis. Beginning with segmentation and feature extraction from diseased lesions, this framework uses autoencoder based classification model. Diseased lesions are segmented using Optimized Region Growing using Grey Wolf Optimization (GWO). Texture features are extracted from the segmented lesion using Gray Level Co-occurrence Matrix (GLCM), and Weber Local Descriptor (WLD). Finally, a reduced feature set is generated through latent representation using the autoencoder. An integrated convolutional neural network is used to classify the diseased lesions from latent representation. The proposed framework significantly outperformed the traditional deep classification strategies, according to experimental findings.

Keywords: Grey Wolf Optimization; Gray Level Co-occurrence Matrix; Weber Local Descriptor;

1. Introduction

Skin is a very essential part of the human body as it protects us from harmful radiation, heat, injuries, and UV radiation infections and also generates vitamin D in the body. It is also significant in maintaining body temperature, which provides good health and avoids skin disease in the body. Skin diseases are considered to be a general type of health illness that is mainly suffered by aged people [6]. These skin diseases are mostly identified by the expertise of doctors

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and also through the skin biopsy results but it leads to high time consumption. This results in requiring automated computer-based systems for identifying and classifying the skin disease using the images for enhancing the diagnostic accuracy and also utilized for handling the scarcity of human experts [7]. Skin disease classification using an image is a challenging task that highly relies on the features of the particular diseases for accurately classifying the disease. But, most skin diseases contain similar characteristics in the visual perspective that in turn make more challenges for selecting the essential features of the image. The accurate analysis of skin diseases from the image is required for enhancing the diagnosis and also speeds up the diagnostic time. This would further result in achieving enhanced and cost-effective treatment for the affected patients[8]. Traditional methods like region and edge-based techniques, clustering methods, and thresholding methods are used for detecting skin lesions. Numerous machine learning techniques are used for developing Computer Aided Diagnostic CADe systems that help to assist doctors through designing the automated detection of skin diseases. Existing machine learning approaches like Artificial Neural Network (ANN) [10], gradient boosting, and Support Vector Machine (SVM)[9] are involved in detecting skin lesions. Gaussian filter is used in the feature extraction of the lesions and also utilized the SVM for classifying the obtained features. The segmentation of skin lesions is performed using Convolutional Neural Network (CNN)[11] based U-net algorithm and also employed several feature extraction techniques like Gabor methods, Histogram of Oriented Gradients (HOG), Edge Histogram (EH), and Local Binary Pattern (LBP) to acquire the shape, texture and color features of the segmented image. These extracted features are further considered for categorizing the benign or melanoma lesions using Random Forests (RF), SVM, Naive Bayes (NB), and K-Nearest Neighbor (KNN) classifiers [10, 11]. Yet, the skin lesions are observed to be varied in their border features, size, and shape, which makes complexity in skin lesion classification [12, 13].

Many deep learning techniques need more computational resources and also require more memory for effective per- performance while tuning the huge parameters [14]. It should enhance the performance by processing the multi-resolution and multi-scale features as the skin lesions images are obtained from various devices along with the changing imaging resolution. The automatic way of skin lesions is also a difficult procedure due to the fine-grained contrast in the skin lesion appearance and heterogeneous visual attributes of skin lesions images[15]. In this work, we try to develop an enhanced skin disease classification model using an improved segmentation approach followed by autoencoder-based classification. The overall contribution of the paper is given as follows.

- A new skin disease classification model using segmentation and autoencoder-based classification.
- Effective segmentation using optimized region growing by tuning the threshold of the segmented image using the GWO algorithm.
- Use of textual features of the segmented lesion using Gray Level Co-occurrence Matrix (GLCM), and Weber Local Descriptor (WLD).
- Use of autoencoder for textual feature reduction for classification using CNN.
- Performance comparison with the different conventional classifiers in the light of several benchmark datasets and quantitative measures.

The following sections are arranged: Section 2 discusses the previous work related to skin disease detection and classification; Section 3 depicts the proposed framework for skin disease classification with feature extraction, and region-growing-based segmentation; Section 4 discussed the Experimental setup and results, and Section 5 concludes the work.

2. Prior Research

The technology will more impact when it will be used practically. The development and usage of deep detection and classification algorithms in skin diseases vast importance. Ahmad *et al.* [1] developed a deep CNN approach for classifying skin disease by learning the discriminative feature with the help of ResNet152 and InceptionResNet-V2 models. Here, the input images were subjected to the deep CNN for learning them into the Euclidean space. Then, the L-2 distance was measured for the respective images, which was utilized for classifying the input images. The analysis has shown that the proposed model has provided high efficiency with better accuracy when compared with existing skin disease classification models. Tang *et al.* [2] have developed a Global-Part CNN Model With Data-Transformed

Ensemble Learning (GP-CNN-DTEL) for classifying skin diseases. The proposed model was estimated and confirmed that the proposed model had secured conventional performance independent of any external data. Adegun *et al.* [3] developed a DenseNet framework model using FCN for automatically detecting and classifying skin lesions with the help of Dermoscopy Images. The suggested system has utilized the hyper-parameters optimization techniques for reducing the network complexity and also for enhancing the computing efficiency. The developed model was also motivated to reuse the features and reduced the requirements on a very small number of parameters along with fewer data. In 2021, Back*et al.* [4] suggested a skin disease classification model with high robustness using the Distilling Deep Neural Network for diagnosing clear and corrupted images. The experimental result has shown that the proposed model has significantly enhanced robustness when compared with other methods. Gu*et al.*[6] investigated a cross-domain skin disease classification using the Progressive Transfer Learning and Adversarial Domain Adaptation along with cycle GAN. The generalization capability of the developed model was evaluated on cross-modality learning tasks, cancer detection, and melanoma detection, which have shown effective performance through resolving the domain shift problem. Much deep learning is integrated and used for classifying the skin disease that is listed in Table 1 with its challenges.

Table 1: Challenges of skin disease classification using dee p learning techniques.

Method	Segmentation used	Base classifier used	Challenges
Deep CNN [1]	No Segmentation	ResNet152	It suffers from generating a reasonable density map to achieve a segmented result similar to the ground truth.
GP-CNN [2]	No Segmentation	CNN	Getting more robustness requires a huge amount of training data.
FCN [3]	Encoder-Decoder Segmentation	Densenet	It does not consider the small objects in the image and often makes smoothening of detailed structures.
KDE-CT [4]	No Segmentation	MobileNet-V3	It consists of hyperparameters that are required to adjust manually based on model datasets.
Cycle-GAN [5]	No Segmentation	ImageNet	The performance of classification is required to be improved as it lacks in considering the discriminant features.

3. Proposed skin disease classification famework

The skin disease classification model is developed by performing region-growing-based segmentation and autoencoder-based classification for achieving accurate skin disease detection automatically. Initially, the skin disease images are collected from the dataset that is subjected to the region growing-based segmentation. The performance of the segmentation is further enhanced by optimizing the thresholding function of the region growing technique. In order to extract the most important features utilising GLCM and WLD, the segmented lesions are taken into consideration. The features from the GLCM and WLD are concatenated and used for the classification. The classification is carried out by the autoencoder technique for identifying the diseased and non-diseased images. The proposed model is shown in Fig. 1.

3.1. Segmentation with Optimized Region Growing

The proposed skin disease classification model utilizes the GWO algorithm for optimizing the thresholding function of the region growing for improving the performance of the segmentation by obtaining accurate segmented results. GWO is encouraged by the hunting behavior of the grey wolf as they are known to be apex predators. Grey wolves are at a high level in the food chain. They contain the dominant social hierarchy at four levels alpha, beta, omega, and delta. The alpha wolf is the dominant wolf. The second level is the beta wolf which is also known as subordinate wolves. The lowest level of the hierarchy is the omega wolf. Finally, the wolf in the pack is not alpha, omega, and beta then it is said to be delta. The three main phases in the hunting behavior of the grey wolves are tracking, chasing, and approaching the prey, pursuing, encircling, and harassing the prey until it stops moving and attacks the prey. These

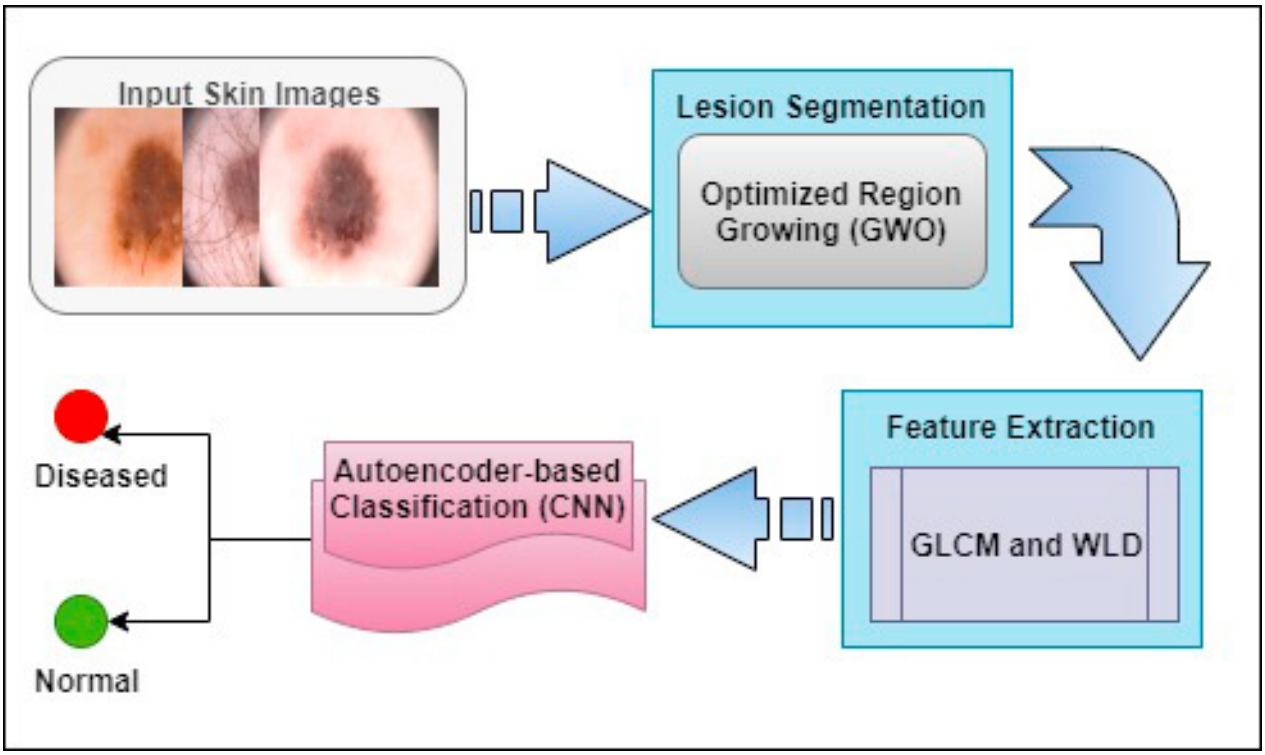

Fig. 1: Proposed Skin Disease classification model with Autoencoder.

α, β, and δ in the grey wolf pack are correspondingly considered the fittest solution, the second-best solution, third-best solution. Then, the remaining wolves in the pack are subjected to omegaω, which needs follow the higher three wolves. The encircling behavior $\vec{E}$ of the grey wolf is equation in the Eq 1.

$$\vec{E} = \left|\vec{C}_1 \cdot \vec{Y}_{pr}(t) - \vec{Y}(t)\right| \tag{1}$$

$$\vec{Y}(t+1) = \vec{Y}_{pr}(t) - \vec{C}_2 \cdot \vec{E} \tag{2}$$

Here, the term $\vec{Y}$ and $\vec{Y}_{pr}$ are correspondingly shows the position of the grey wolf and position of the prey. Term t shows the current iteration. The coefficient vectors are denoted as $\vec{C}_1$ and $\vec{C}_2$, which are measured as in the Eq 3 and Eq 4.

$$\vec{C}_1 = 2\vec{d} \cdot \vec{m}_1 - \vec{d} \tag{3}$$

$$\vec{C}_2 = 2 \cdot \vec{m}_2 \tag{4}$$

Here, the components of $\vec{d}$ decreases from 2 to 0 in the iteration at the linear manner and the terms $\vec{m}_1$ and $\vec{m}_2$ are described as the random vectors that lies in the range of[0, 1]. The best search agents are followed by the other search agents. So, the encircling behavior of alpha, beta and delta wolves is computed in the Eq 5.

$$\begin{aligned} &\vec{E}_\alpha = \left|\vec{C}_1 \cdot \vec{Y}_\alpha - \vec{Y}\right|, \vec{E}_\beta = \left|\vec{C}_2 \cdot \vec{Y}_\beta - \vec{Y}\right|, \\ &\vec{E}_\delta = \left|\vec{C}_3 \cdot \vec{Y}_\delta - \vec{Y}\right| \end{aligned} \tag{5}$$

$$\begin{aligned} &\vec{Y}_1 = \vec{Y}_\alpha - \vec{E}_1 \cdot \left(\vec{E}_\alpha\right), \vec{Y}_2 = \vec{Y}_\beta - \vec{E}_2 \cdot \left(\vec{E}_\beta\right), \\ &\vec{Y}_3 = \vec{Y}_\delta - \vec{E}_3 \cdot \left(\vec{E}_\delta\right) \end{aligned} \tag{6}$$

The three positions of the best search agents (α, β and δ) are computed that is used for updating the final position of the grey wolf. This is shown in the Eq 7.

$$\vec{Y}(t+1) = \frac{\vec{Y}_1 + \vec{Y}_2 + \vec{Y}_3}{3} \tag{7}$$

The updated position of the grey wolf is indicated as $\vec{Y}(t+1)$. Thus, the best optimal solution is attained as $\vec{Y}_\alpha$. The region growing [21] employs the input images $M_r^{data}$for performing the segmentation in the proposed skin disease classification model. Here, the performance of the region growing is further improved by optimizing the thresholding functionδ of region growing using the developed GWO algorithm. The region growing generates the image regions by clustering the homogeneous pixels. It is performed by selecting the seed pixel and iteratively adding the new relevant pixels into the seed until the segmentation criterion is satisfied with the enclosed segments. Initially, the input pre-processed image M_r^{data} with its area is depicted as$R$. The pre-processed images $M_r^{data}$are segmented into the number of z sub-regions. The divided sub-regions are denoted as $R_1, R_2, \cdots, R_v$, which needs to fulfill the following conditions.

- For $R_1, R_2, \cdots, R_v$, where, R indicates the connected regions, $\bigcup_{k=1}^{f} R_K = R$.
- $P(R_P) = TRUE$;, for any $P, K, P \neq K, R_P \bigcap R_K = \phi$,
- and $R(R_P \bigcup R_K) = FALSE$.

Here, the term $P(R_P)$ refers to the gray level value of the set R_K and f is the total number of pixels in the image. Initially, the seed point is chosen and concatenated with the seed points that carry the pixel value, which satisfies the following condition with respect to user defined threshold, δ.

$$|G(c,d) - Mean|_{(c,d)\in R} < \delta, \tag{8}$$

where, $G(c,d)$ denotes the pixel value in the coordinate (c,d) and $Mean$ is the mean pixel by pixel values within the image. $Mean$ can be calculated as, $Mean = \frac{1}{f}\sum_{(c,d)\in R} G(c,d)$. The threshold, δ and the seed selection are the two factors that play a major role in enhancing the segmentation process. The output of the segmentation based on optimized region growth is achieved and denoted as M_i^{regw}. The objective function of the proposed skin disease classification model is to maximize the accuracy and dice-coefficient which can be calculated as follows.

$$Ofun_{(2)} = \arg\min_{\{\delta\}} \left(\frac{1}{ay + dc} \right) \tag{9}$$

Here, ay and dc denotes two objective parameters, accuracy and dice-coefficient of the segmented image, that needs to be optimized.

3.2. Feature Extraction

In the proposed skin disease diagnosis model, the essential texture features are extracted from the segmented disease lesions. We use GLCM[22] and WLD[19] for textual feature extraction. GLCM utilizes the segmented skin disease images M_i^{regw} for extracting the texture features such as Contrast, Energy, Dissimilarity, Entropy and Correlation. The obtained parameters are used to evaluate image alignment, and the corresponding features are extracted in the GLCM, which can be denoted by F_h^{glcm}, where, $h = 1, 2, \ldots, H$ and H denotes the total number of extracted texture features using the GLCM methods. WLD is a feature extraction technique that determines the ratio of pixel intensity variations in order to extract texture information from an image.Under visual perception, this is referred to as stimulus information. The ratio of change in pixel intensity between the centre and its neighbours is calculated using differential excitation. There are local salient visual patterns that have been identified. The features extracted using WLD is denoted as F_o^{wld}, where, $o = 1, 2, \cdots, O$ and the total number of features extracted is given as O. Finally, the 'total number of features' is represented as $F_g^{EF} = \left\{F_h^{glcm}, F_o^{wld}\right\}$, where, $g = 1, 2, \cdots, G$. In this proposed model, the total number of features extracted is given as G. All total we extract 24 GLCM features and 65536 WLD features which we concatenate to form a large feature vector of size 65,560. We next reduce the vector using latent representation before feeding into classifier. A synopsis of the features used is reported in Table 2.

Table 2: Features that are extracted using feature extraction methods

Feature Vector	Definition	Method used
Contrast	pixels with known constant values for their pixel intensities	GLCM
Energy	Uniformness in the image with square elements summation	GLCM
Dissimilarity	In contrast, weights grow dramatically when a pixel moves away from the diagonal.	GLCM
Entropy	Loss of data in a signal which are transmission measure	GLCM
Correlation	Correlate a pixel to its neighbor pixels	GLCM
Differential excitation	Ratio of pixel intensity change between the centre and its neighbours	WLD

3.3. Feature Reduction using Autoencoder

The autoencoder [20] is utilized in the developed skin disease classification,a coder is a process that occurs between the input layer and the hidden layer. The image is reconstructed after the compressed features from the hidden layers are forwarded to the output layer. A decoder is used to process features between the hidden layers and the output layers. In the autoencoder approach, the loss ratio is the most important parameter, which must be kept to a minimum to achieve accurate classification. The loss function is used to determine the weight parameters in the autoencoder model. Finally, the value of F_g^{EF*}approaches to input features F_g^{EF}that minimizes the loss rate. This case is given in Eq 10.

$$H\left(F_g^{EF}, F_g^{EF*}\right) = F_g^{EF} - \left(F_g^{EF}\right)^2 \tag{10}$$

$$x = \sigma\left(wF_g^{EF} + b\right) \tag{11}$$

$$F_g^{EF*} = \sigma'\left(w'F_g^{EF} + b'\right) \tag{12}$$

Here, term $b$represents the bias vector and$w$ represents the weight matrix. The termσdenotes the activation function value. The output layer value $F_g^{EF*}$is determined using Eq 11 and the hidden layer value $x$is found according to Eq 12.

3.4. Classification

The proposed autoencoder model can be worked out the principles of Convolution Neural Network (CNN),input layer with segmented images,convoluted with 3 hidden layers and fully connected layer with linear activation function.

4. Experimental setup

The proposed skin disease classification model is executed in Python, and evaluated the performance using several performance assessment measures.The efficiency of the autoencoder-based skin disease classification is compared with several deep classification techniques like Cycle-GAN [5],GP-CNN [2],KDE-CT [4],CNN [16], RNN [18], and LSTM [17].

4.1. Dataset description

The Skin disease images are collected from open source dataset ph^2 [1] with collection of 200 images. It contains images of the diseases like Atypical Nevus 80, Common Nevus, 80 atypical nevi, and 40 melanomas. The dataset have valid ground truths derived by the experts.

[1] https://www.fc.up.pt/addi/ph2%20database.html: Access Date: 2021-10-25

4.2. Intermediate results

The segmented results of the proposed region growing-based skin disease segmentation model based on its dataset is shown in Fig 2. The features selected after the segmentation are reported in below Fig 3

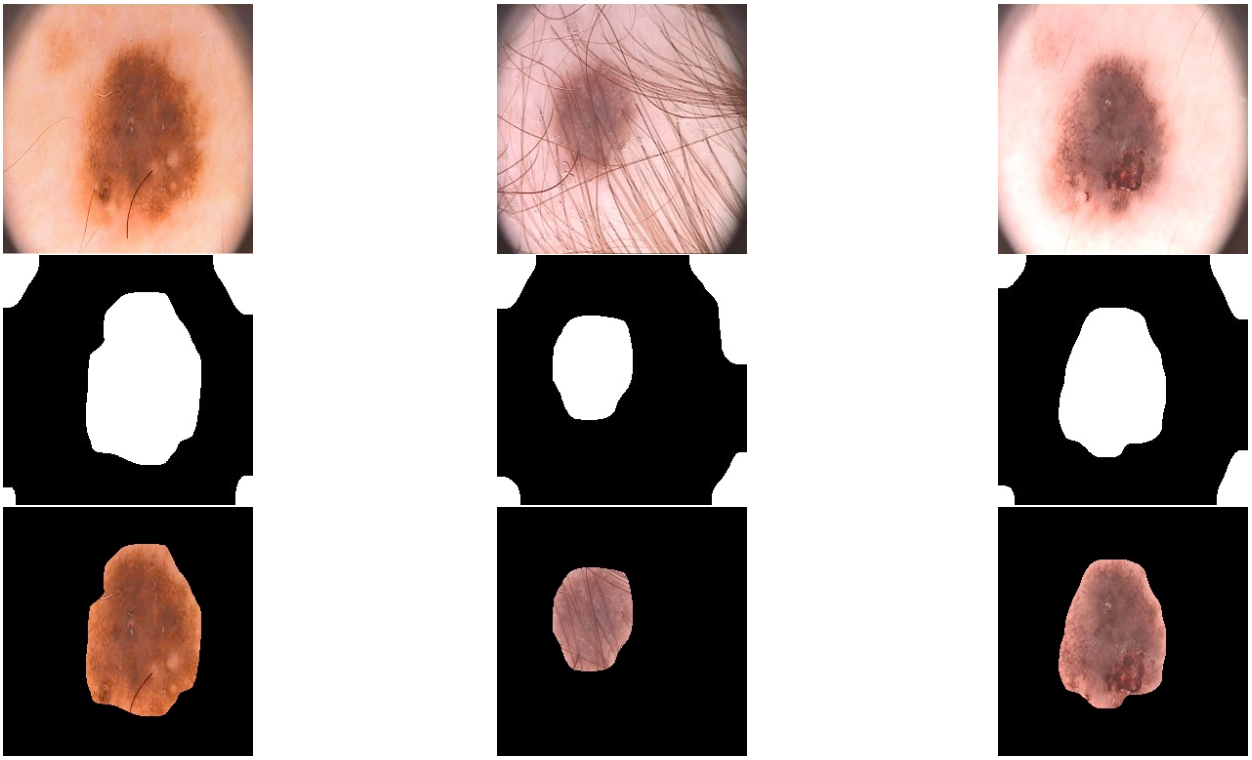

Fig. 2: Actual Images, Pre-processed images and Segmented images using Region Growing

4.3. Performance analysis

The proposed skin disease classification model's performance is assessed by comparing it to various classifiers depicted in Fig 4 at various learning percentages. At a learning percentage of 85, the autoencoder performs better than the CNN, RNN, and LSTM in terms of accuracy by 2.1, 5.55, and 7.9 percent, respectively. The performance of the proposed algorithm secures the highest level even in the increasing learning percentages, which can be observed through all the quantitative measures. According to the obtained dataset, the overall performance of the proposed skin disease classification model outperforms other conventional methods. The proposed skin disease classification model's overall performance is evaluated by comparing it to the various classifiers listed in Table 3. The performance of the autoencoder provides 6.78%, 7.2%, and 3.68% enhanced precision than the CNN, RNN, and LSTM, respectively. The performance of the autoencoder obtains the highest values in all the quantitative measures among the conventional classifiers. Therefore, When compared to existing methods, the proposed skin disease classification improves performance.

5. Conclusion

In order to detect skin disease and obtain a higher level of accuracy, the proposed work created a novel skin disease classification model by performing enhanced region growing-based segmentation and autoencoder-based classification. For the classification of skin diseases, the GLCM and WLD features were combined. To distinguish between

gray_mean	gray_std_dev	adaptive_mean	adaptive_std_dev	clahe_mean	clahe_std_dev	sobel_std_dev	sobel_mean	er_mean	er_std_dev	Histeq_mear
151.316047	44.423817	120.665757	84.434148	148.662867	52.961959	419.088120	-6.811344	130.029735	48.129697	128.647381
184.919105	59.332650	163.409080	93.487688	160.838389	57.546949	514.283345	-39.806362	161.169942	65.800981	128.600646
158.995536	30.988217	139.850506	66.682618	157.489118	45.605338	333.264595	-5.169643	141.925303	33.741320	129.292391
188.841677	34.526455	180.621173	57.355211	172.013453	46.221867	347.432511	4.582111	170.598433	44.940742	129.362265
163.527144	32.845150	138.974071	73.357626	158.702746	43.005965	392.251704	24.764489	147.180046	36.150785	128.864796

Fig. 3: Sample Feature values from images

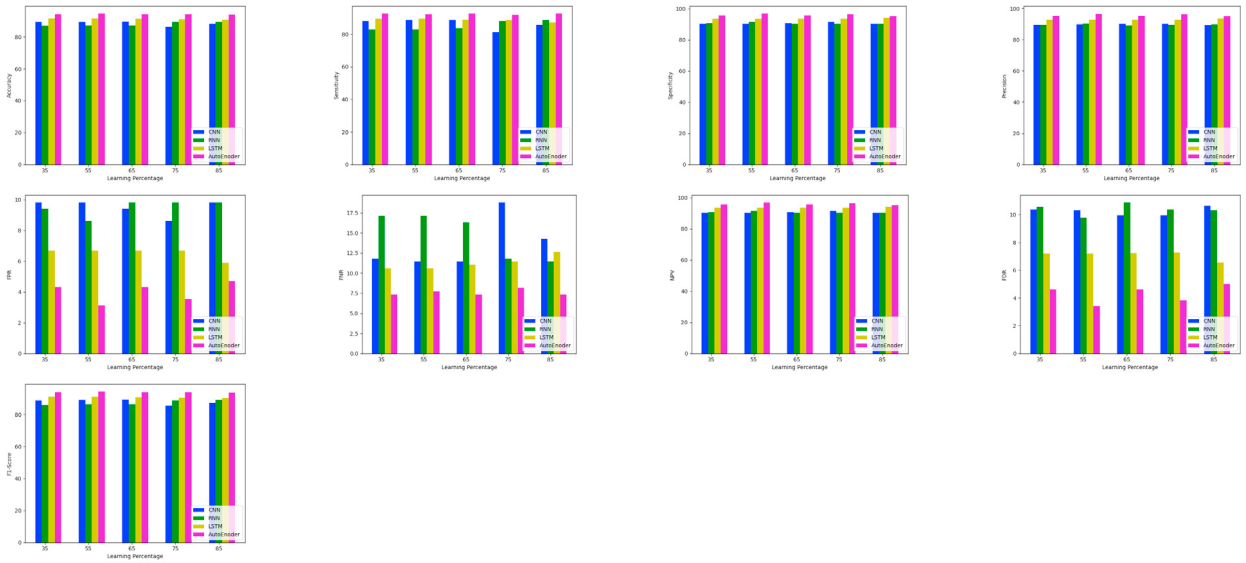

Fig. 4: Proposed model Performance Measures like Accuracy,F1-Score,FDR,FNR,FPR,Precision,MCC,NPV,Sensitivity and Specificity

Table 3: Proposed model performance Comparison with Cycle-GAN,GP-CNN,KDE-CT, CNN,RNN and LSTM

Measures	Cycle-GAN [5]	GP-CNN [2]	KDE-CT [4]	CNN [16]	RNN [18]	LSTM [17]	Proposed
“Accuracy”	0.910744	0.91939	0.929816	0.864	0.892	0.91	**0.942**
“F1-score”	0.629017	0.649701	0.675205	0.854077	0.888889	0.906054	**0.939457**
“FDR”	0.51755	0.494957	0.467259	0.099548	0.103734	0.07265	**0.038462**
“FNR”	0.096503	0.08951	0.078322	0.187755	0.118367	0.114286	**0.081633**
“FPR”	0.096923	0.089231	0.080839	0.086275	0.098039	0.066667	**0.035294**
“Sensitivity”	0.903497	0.91049	0.921678	0.812245	0.881633	0.885714	**0.918367**
“Specificity”	0.903077	0.910769	0.919161	0.913725	0.901961	0.933333	**0.964706**
“Precision”	0.48245	0.505043	0.532741	0.900452	0.896266	0.92735	**0.961538**
“NPV”	0.989427	0.990268	0.991551	0.913725	0.901961	0.933333	**0.964706**
“MCC”	0.61693	0.637791	0.663961	0.730758	0.783945	0.820566	**0.88471**

images with and without disease, the classification is carried out using the latent representation generated through the autoencoder technique. Experimental results showed that the proposed framework achieved better performance than CNN, RNN, and LSTM classifiers. Work is on to devise a better consensus-driven classification model with an optimised segmentation step.

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