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Early Skin Disease Identification Using Deep Neural Network

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Abstract: Skin lesions detection and classification is a prominent issue and difficult even for extremely skilled dermatologists and pathologists. Skin disease is the most common disorder triggered by fungus, viruses, bacteria, allergies, etc. Skin diseases are most dangerous and may be the cause of serious damage. Therefore, it requires to diagnose it at an earlier stage, but the diagnosis therapy itself is complex and needs advanced laser and photonic therapy. This advance therapy involves financial burden and some other ill effects. Therefore, it must use artificial intelligence techniques to detect and diagnose it accurately at an earlier stage. Several techniques have been proposed to detect skin disease at an earlier stage but fail to get accuracy. Therefore, the primary goal of this paper is to classify, detect and provide accurate information about skin diseases. This paper deals with the same issue by proposing a high-performance Convolution neural network (CNN) to classify and detect skin disease at an earlier stage. The complete methodology is explained in different folds: firstly, the skin diseases images are pre-processed with processing techniques, and secondly, the important feature of the skin images are extracted. Thirdly, the pre-processed images are analyzed at different stages using a Deep Convolution Neural Network (DCNN). The approach proposed in this paper is simple, fast, and shows accurate results up to 98% and used to detect six different disease types.

Keywords: Convolution neural network (CNN); skin disease; deep learning (DL); image processing; artificial intelligence (AI)

1 Introduction

Skin is the most sensitive part of the human body and enhances its appearance. Skin disorder is one of the extremely widespread and impact on the appearance of the skin. The main reason of the skin diseases are fungus, allergy, bacteria, and viruses, etc. This may be the reason for the transformation of skin texture and color. Later stage, this may be the reason for chronic, infection, and disease. In 2013, the population of India

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affected by skin disease was reported to be approximately 15.1 crores, with a prevalence rate of 10%. According to estimates, 18.8 crore people will be affected by skin disease by 2015. The skin diseases are broadly classified in three types as given below:

a) Internal and External: Skin disorders that grow within the body are known as internal involving hormones and body glands, such as acne. Skin disorders grow on the skin and manifest themselves on the surface are known as external one involving air pollution or sun exposure, such as rashes.
b) Chronic and acute: Skin diseases may be chronic, like psoriasis and atopic eczema, or uncommon, like sweet syndrome and fuji disease.
c) Primary and Secondary: The skin disease may be either primary or secondary. Spots, pimples, plaque, discoloration, nodule, tumor, vesicle, pustule, cyst, and bulla are examples of primary skin disease, while crust, decay, excoriation, scale, ulcer, fissure, induration, atrophy, maceration, umbilication, and phyma are examples of secondary skin disease.

Some of these diseases may take lots of time to show symptoms and are difficult to detect. The lack of medical knowledge may be the reason for severe disease. In most of the cases, it is difficult to diagnose it with bare eyes. Therefore, he/she recommend costlier laboratory and laser tests to diagnose it properly. Some of these tests may be the reason for some other harmful effects on human skin. To eliminate such expenses and ill effects of tests on the human body, an automated system is proposed in this paper to detect and classify skin disease.

Therefore, it is mandatory to earlier detect, reduce impact and stop spreading otherwise it may be the reason for health problems. Most ordinary people are unaware of skin disease. In some cases, it has been observed that the skin disease shows symptoms a month later in the final stage. This may be the reason for the lack of knowledge about skin disorders. In some situations, it has been observed that even the skin specialist is not able to diagnose it and that leads to costlier laboratory tests. This is the main reason to develop such a system that helps to earlier detect skin disease based on the skin texture. Images are one of the best sources for such systems.

In most cases, early detection and care are sufficient to fully cure the illness but early identification of the type of ailment is critical. Tests conducted with the naked eye have several disadvantages, including precision inconsistencies, the human observer's caution, and so on. Computer-assisted techniques can study and track the subsurface structures of pores and skin disease more effectively. This approach allows for a deeper understanding of rare disease, their appearance, and characteristics. Furthermore, dermatologists are in short supply, especially in rural areas, and consultations are expensive. Furthermore, the traditional approach can result in infections and pains. Disease should be identified automatically from photographs in dermatology to provide precise, early, and objective diagnoses.

This advances to a skin disease diagnosis approach centered around computer vision. The diagnosis of these diseases may also be aided by automated classification of disease, which eliminates the hurdles of costly treatment. Furthermore, automatic disease classification diagnosis is more cost-effective than conventional diagnosis. Picture partitioning is the method of splitting a digital image into several regions or artifacts and processing them separately depending on the need and function. It easily streamlines the analysis and classification. Pixels around the similar section have the same attributes, although clusters have different characteristics.

Various deep learning models have been proposed to address various issues different field such as agriculture [1–7], weed growth [8–11], soil [12,13], object detection [14] and in various robotic based system [15]. Here, this paper tackle skin disease issue with deep learning model and image processing.

In this paper, the skin images are used to identify and classify skin disease. The main contributions of the paper are:

- In proposed techniques, the CNN is tuned with different values of hyper-parameters to get better results.
- Here, a vegetation/semantic segmentation to resolve the issue of normal segmentation techniques.
- Vegetation Segmentation is used to reduce the noise in the image and focuses on the disease part.
- The target skin disease is processed with proposed method to enhance the accuracy.

The complete paper is explained in different folds: Section 2 is concerned about the state-of-the-art review. Section 3 explains about material method and process. Section 4 describes the proposed model and mathematical transformation. The result and discussion are explained in Section 5. Section 6 describes the conclusion and future work.

2 Related Work

Lots of artificial intelligence (AI)-based techniques and methods are proposed by researchers to identify and classify skin diseases which are discussed in this section. The skin disease recognition and classification technique are given below:

A system is proposed in [16] that consists of two stages to detect skin disease using color images: firstly, to detect the infected skin by use of color image and apply k-mean clustering with color gradient techniques to identify it. Secondly, Artificial Neural Network (ANN) is used to classify diseases.

The image features are extracted after prepossessing the image and the same features are used to predict the type of disease [17]. The accurateness of the technique depends on the number of extracted features. These features are inputted to feed-forward ANN for training and testing. Total nine different diseases are classified here with an accuracy of 90%.

In this paper, the lesion part and background part are separated using different segmentation methods and after segmentation, the lesion part is processed with image processing techniques [18]. After experiments, the author concludes that the Multilevel thresholding has a better accuracy rate.

A specialized algorithm is applied to a given image dataset to detect diseases of dark skins [19]. The support vector machine is used in [20,21] to detect skin disease. Computer vision and machine learning techniques are combined to detect skin disease with a 95% accuracy rate. The underlying deep learning technique with the unique visual feature is applied in [22,23] to diagnose skin diseases.

In [24–27] the ANN is applied to the image dataset to diagnose skin disease. The segmentation based on two feature sets is employed with the Sobel operator in [28] to diagnose three different skin diseases. The deep neural network is used in [29,30] to classify four different skin diseases. In this GoogleNet Inception and V3 packets are used to classify the image and attain an accuracy of 86%.

A rule-based expert system is developed in [31] that uses forward chaining with a depth-first search algorithm. Image processing and ANN are used in [32] to detect skin disease. In this, some histopathological attributes are also involved with image processing for accurate results. A data mining technique is involved with a skin detection system to enhance its accuracy with the choice of attribute [33].

A review of different Skin Disease classification technique with accuracy is described in "Tab. 1".

Table 1: Review of skin disease classification techniques

Ref.	Year	Evaluating technique	Performance
[34–36]	2015, 2009, 2012	Feed Forward Neural Network (FFNN)	-
[37]	2012	ANN	92%
[38]	2011	Image Processing	84%,
[39]	2013	MobileNet	94.4%.
[40]	2019	Multiclass Support Vector Machine(SVM)	97.2%.
[41]	2019	SVM	95%.
[42]	2016	Machine Learning	–
[43]	2016	Feature Extraction	-
[44]	2019	CNN	94.3%, 91.2%, and 92.9%
[45]	2020	Navier Bayes	94%
[46,47]	2021	DenseNet201 and ImageNet	–
[48]	2021	Deep Learning	-
[49]	2018	Neural Network with Optimization	99%
[50]	2020	-	-
[51]	2021	histogram-based statistical method	77%, 67%, 92%
[52]	2021	Capsule neural network	–
[53]	2020	Capsule neural network	85.69%
[54]	2019	Deep-learning Model	70–80%
[55–57]	2021, 2018, 2019	Deep Learning	85%
[58]	2017	Deep Learning	89%
[59]	2020	CNN	80.2%
[60]	2020	5-layer CNN	95%
[61]	2019	14-layer CNN	97.78%
[62]	2020	Distributed Learning System (DLS)	99.77%
[63]	2020	Deep Residual Network	88.7%.
[64]	2020	Local binary pattern (LBP) Resnet-50 and DenseNet-121	-.
[65]	2020	CNN, K-nearest neighbour (KNN), and SVM	88.4%
[66]	2020	AlexNet	97.9% 97.4%
[67]	2018	Alex Net	94.2%
[68]	2019	VGG, ResNet and DenseNet	90%.

The next section of the paper is concerned with the dataset and proposed methodology.

3 Material and Method

In this section, for validating the dataset of skin images with state-of-art methods and models are presented.

3.1 Dataset

A dataset consists of around 2000 skin disease pictures collected from a standardized dataset Dermnet [69] containing 1800 training data pictures and 200 data test pictures, as shown in Tab. 2 and Fig. 1. The dataset comprises distinct classes of disease. Different classes are infected skin, and one stable class is given in the list:

Table 2: Dataset description [69]

Disease type	Dataset size (*n*)	dataset (%)	Images for test (*n*)	Priority
Acne and rosacea	312	15	100	low
Actinic keratosis basal cell carcinoma	288	14	88	moderate
Eczema	300	15	100	low
Nail fungus	261	13	61	moderate
Psoriasis	352	17	150	moderate
Seborrheic	342	16.52	100	Low
Light Diseases and Disorders of Pigmentation	145	7.25	45	low

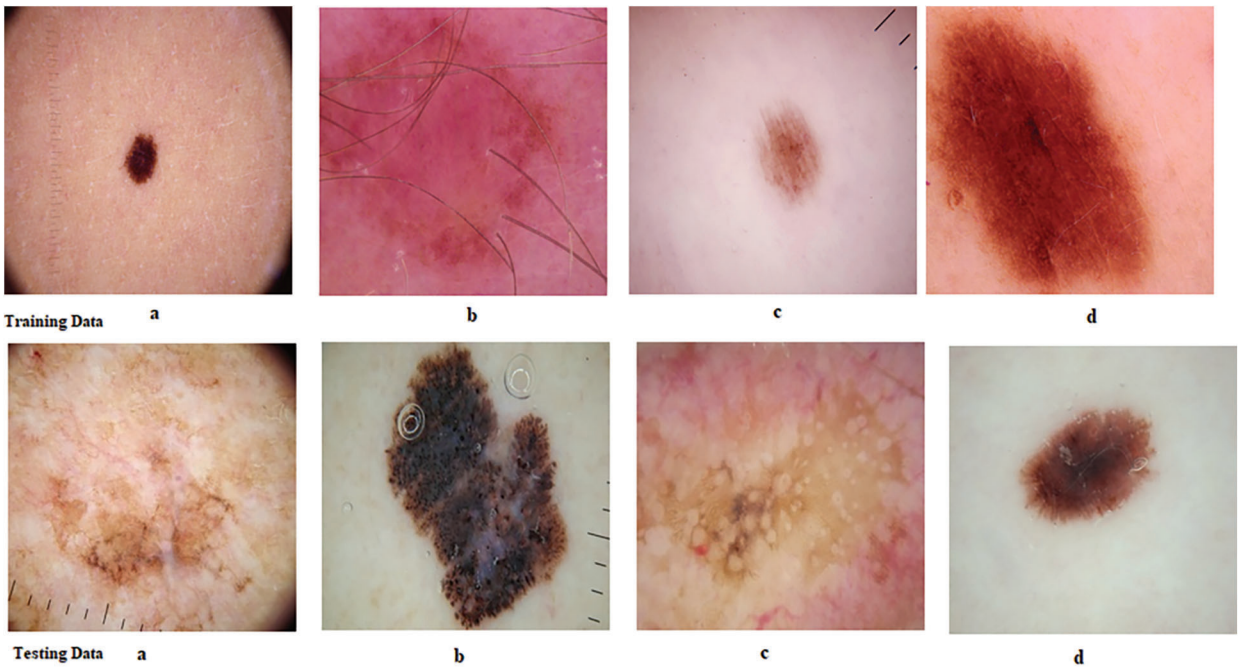

Figure 1: Sample skin diseases

Fig. 1. shows the reference images of skin diseases from dataset. The experiment is performed with 2000 sample images. Almost 1600 images are used to train the model and 600 images are used to test the model. The experiment is performed with different training and testing ratios but one 80:20 results are shown in this paper.

The next section is dealt with proposed methodology, mathematical model and detection algorithm:

4 Proposed Methodology

The disease detection methodology starts with the first phase of data pre-proceeding and labeling. Secondly, pre-processed data is classified using a Convolution neural network. "Fig. 2: Laid down the complete process of disease classification and detection. The CNN is tuned on hyperparameters which are based on the training of proposed network and numbers of hidden layer. Here in this paper, the hyperparameter are chosen based on the network which used to classify the images. The complete Convolution neural network (CNN) layout is shown in Fig. 3 and description is given in Tab. 3.

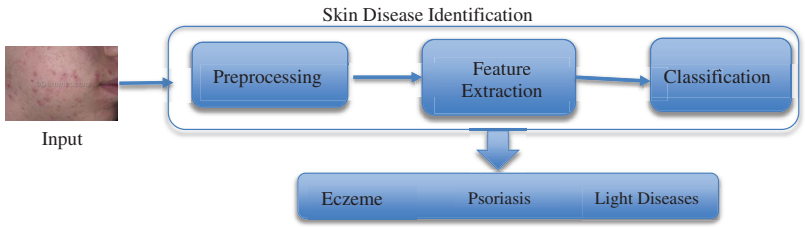

Figure 2: Proposed methodology

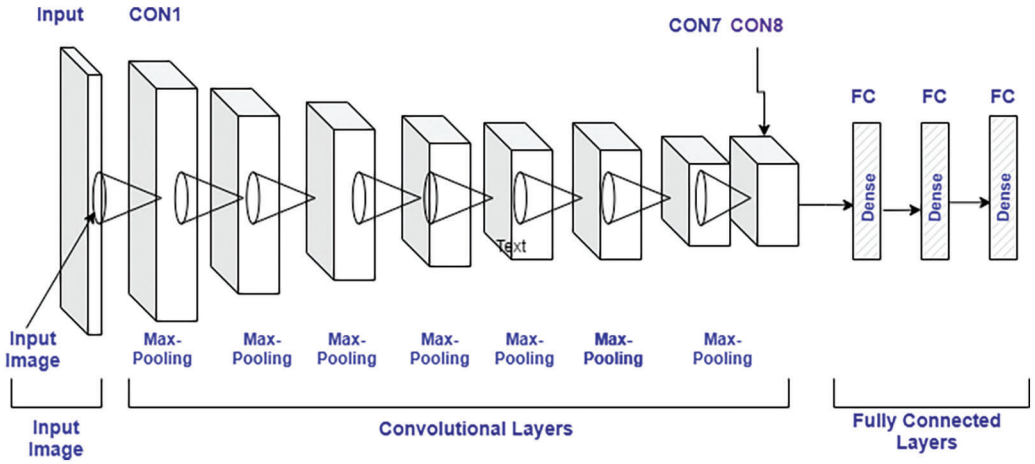

Figure 3: CNN model architecture

4.1 Image Pre-Processing and Labelling

This is an initial phase, where the raw image dataset is pre-processed to remove noise before inputting it to the Convolution neural network classifier. It must for a model to analyze the structure of the network and dataset to generate better outcomes. Therefore, the dataset is preprocessed initially to collect appropriate features of images which can be used by the model to accurately diagnose or predict the actual outcomes. Here in pre-processing, firstly, the size of each image is normalized as per requirement which is 256*256 pixels. The image size is defined during network design and act as input node. The same is used

to train the model to achieve consistent results. The python libraries are utilized to perform the same task with maximum accuracy. Secondly, all images are converted into grey images.

Table 3: CNN tuning parameter

Parameter	Description
Convolution layer	10
Max pooling layer	10
Drop-out rate	0.25
Network weight assigned	Uniform
Activation function	Relu
Learning rates	0.01, 0.01, 0.1
Epochs	50, 100, 150
Batch size	36, 64, 110

The pre-processing stage is considered as a phase that extracts image features to train the model. These training features are the reason for accurate prediction. After pre-processing, the data labeled with the correct acronym. After this data is segregated into different classes which can be used for testing.

4.2 Mathematical Representation of Classification

Here, the Convolution neural network (CNN) is utilized for classification, one of the most prominent technologies used at present. Here, the model is accomplished with the feature extracted in the previous phase. In the CNN, the image dataset is processed in different layers and each layer has the following sub-layers:

a) Convolutional Layer

The main operation in the convolutional layer is convolution in which the input image is mapped with a filter of m*m and generates outcome feature maps. The outcome of the convolutional layer is expressed by Eq. (1)

$$A_n^m == \mathrm{f}\left(\sum_{\mathrm{k}\in \mathrm{L_n}} \mathrm{A_{kn}^{m-1}} * \mathrm{M_{kn}^m} + \mathrm{C_n^m}\right) \tag{1}$$

where,

A_n: Outcome feature maps,

L_n : Input maps,

M_{kn} : Kernel of convolution,

C_n : Bias term.The degree of final feature map is expressed by,

$$\boldsymbol{N} = \frac{(\mathbf{X} - \mathbf{M} - \mathbf{2Y})}{\mathbf{T}} \tag{2}$$

where,

N: output height/length

X : input height/length

M: filter size,

Y: padding,T: Stride.

Here, padding can be used to store the output. The padding is expressed by Eq. (3):

$$\boldsymbol{Y} = \frac{(\boldsymbol{M} - \mathbf{1})}{\mathbf{2}} \tag{3}$$

where, M: filter size.

- ReLU Layer: This also plays an important in CNN and is also known as the Activation layer. This layer is next to the convolution layer and the output of the same will be input to the ReLU. This layer creates linearity in the convolutional process. So, each convolutional layer is associated with a ReLU layer. The important task of this layer is to update all negative activation to zero and thresholding which is given by f(p) = max(0, p). This layer helps the system to learn quickly and remove gradient problems. ReLU activation function is well designed for multiclass classification.
- Max-Pooling Layer: This layer generates the reduce sized output after maximizing the elements of each block. This layer also controls the overfitting problem without the learning process.
- Dropout Layer: This layer is used to drop out the input elements having a probability less than a certain value and this process is a part of the training phase.
- Batch Normalization Layer: This layer plays an important role in between the convolutional and ReLU layer. This layer is used to enhance the training speed and reduce sensitivity. This layer performs different operations (subtractor, division, shifting, and scaling). The activation layer to normalize its value. Firstly, the activation is subtracted with mean, and divided by the standard deviation which is followed by fluctuating by α and then scaled by Θ. The batch normalized outcome, B_k is expressed by the Eqs. (4)–(7),

$$\begin{aligned} \boldsymbol{B_k} &= \mathrm{D}\boldsymbol{O}_{\boldsymbol{\theta_z}} \times (\boldsymbol{A_k}) \\ &\equiv \boldsymbol{\theta}\widehat{\boldsymbol{A_k}} + \boldsymbol{D} \end{aligned} \tag{4}$$

where $\hat{\mathbf{A}}_{\boldsymbol{k}}$ is the normalization of activation A_k.

$$\hat{\boldsymbol{A}}_{\boldsymbol{k}} = \frac{\boldsymbol{A_k} + \boldsymbol{U_D}}{(\boldsymbol{\sigma_D^2} + \boldsymbol{\varepsilon})^{\mathbf{1/2}}} \tag{5}$$

where,

ε : constant

U_D: Mini-batch mean

$\sigma_D{}^2$: Mini-batch variance given by,

$$\boldsymbol{U_D} = \frac{\mathbf{1}}{\mathbf{d}} \sum_{\mathbf{k=1}}^{\mathbf{d}} \mathbf{A_k} \tag{6}$$

$$\boldsymbol{\sigma_D^2} = \frac{\mathbf{1}}{\mathbf{d}} \sum_{\mathbf{k=1}}^{\mathbf{d}} (\mathbf{A_k} - \mathbf{U_D})^{\mathbf{2}} \tag{7}$$

b) Fully Connected Layer

Here, the neurons of the next layer are linked with neurons of the previous layer and produced a vector, and the vector dimensions represent the number of classes.

c) Output Layer

This layer is a combination of softmax and classification. In this layer, firstly, the softmax is used to distribute the probability and the classification is carried out by the network. The softmax is defined by Eq. (8)

$$\boldsymbol{P}(\boldsymbol{v_r}\ |\boldsymbol{A},\ \boldsymbol{\theta}) = \frac{\boldsymbol{P}(\boldsymbol{A},\ \boldsymbol{\theta}|\boldsymbol{v_r})\ \boldsymbol{P}(\boldsymbol{v_r})}{\sum_{n=1}^{M} \boldsymbol{P}(\boldsymbol{A},\ \boldsymbol{\theta}|\boldsymbol{v_r})\boldsymbol{P}(\boldsymbol{v_r})} \tag{8}$$

where, $0 \leq \boldsymbol{P}(\boldsymbol{v_r}|\mathbf{A}\ \boldsymbol{\theta}) \leq \mathbf{1}$ and $\sum_{\mathbf{n=1}}^{\mathbf{M}} \mathbf{P}(\mathbf{v_r}|\mathrm{A},\ \boldsymbol{\theta}) = \mathbf{P}(\mathbf{A}, \boldsymbol{\theta}\ |\mathbf{v_r})$ is the conditional probability and class prior probability. Eq. (9) can also be

$$\boldsymbol{P}(\boldsymbol{v_r}|\boldsymbol{A}, \boldsymbol{\theta} = \frac{\mathbf{exp}[\mathbf{d_r}(\mathbf{A},\ \boldsymbol{\theta})]}{\sum_{n=1}^{M} \mathbf{exp}[\boldsymbol{d_n}(\boldsymbol{A},\ \boldsymbol{\theta})]} \tag{9}$$

written as follows, where

$$\boldsymbol{d_r} = \mathbf{ln}\ (\boldsymbol{P}(\boldsymbol{A},\ \boldsymbol{\theta}|\boldsymbol{v_r})\ \boldsymbol{P}(\boldsymbol{v_r})) \tag{10}$$

4.3 Skin Lesion Detection Algorithm

The algorithm initiates with images $\boldsymbol{IN_{RGB}}$. After that $\boldsymbol{IN_{RGB}}$ is segmented into $\boldsymbol{MS_{mask}}$. The $\boldsymbol{MS_{mask}}$ is further partitioned into several regions $\boldsymbol{R_{sep}}$. Afterward, it chooses the Region of Interest (RoI) and the same is used to identify skin disease. The proposed algorithm is given in below:

Algorithm 1: Disease Detection

Input: IN_{RGB} Image with Disease

Output: Disease Recognition.

a) For given IN_{RGB} , produce the masking (MS_{mask})

b) Cover IN_{RGB} With MS_{mask}

c) Divide MS_{mask} into smaller regions K_{tiles} (square tiles);

d) for (R_{sep} in MS_{mask}) dos

Classify R_{sep} into MS_{mask} skin lesion.

if R_{sep} is disease then Identify Lesion

e) end

The next section discusses the result analysis and their interpretation.

5 Result Analysis and Discussion

The research is carried out with the help of Co-Lab-based Graphics Processing Unit (GPU) and python-based karas libraries are used to implement the complete approach. Here in this research, experiments are performed with varying the batch size, epoch, and learning rate. The experiment is performed with two epoch sizes i.e., 50 and 100, and three learning rates i.e., 0.1,.001, and .0001 learning rates. The model performance is measured on different performance indicators such as accuracy, precision, recall and F1-Score. The results are laid down below:

The objective here is to observe the effect of Epochs on device efficiency. An epoch is a complete introduction to a learning machine of the data set. In this research, the experiment is conducted with 50 and 100 epochs size. "Fig. 4: shows the test with 50 epochs" and "Fig. 5: Shows 100 epoch sizes with a learning rate of 0.0001". Both show an accuracy rate that is 98.02% and 98%.

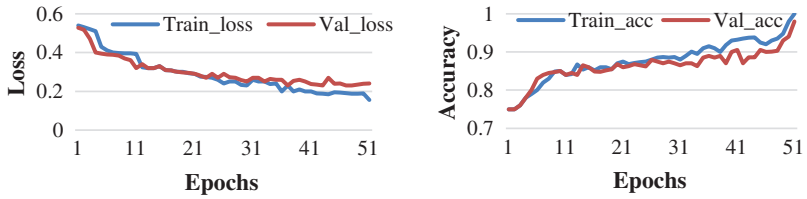

Figure 4: Accuracy and loss learning rate 0.0001

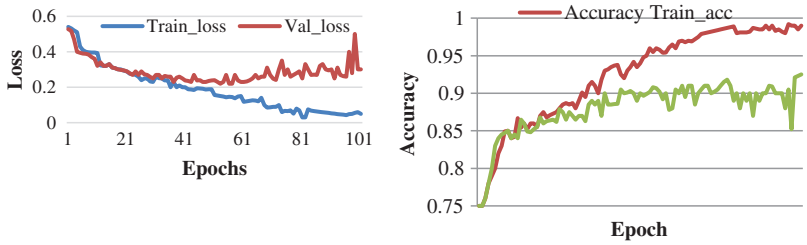

Figure 5: Accuracy and loss with learning rate 0.0001

It is possible to assume that more times will provide a higher percentage of correctness centered on the investigation procedure. But the number of epochs is getting longer, the longer the training step involves.

Here, the experiment is conducted with 50 and 100 epochs size. "Fig. 6: shows the test with 50 epochs "and "Fig. 7**:** shows 100 epoch sizes with a learning rate of 0.001". Both show an accuracy rate that is 98.07.% and 98.25%.

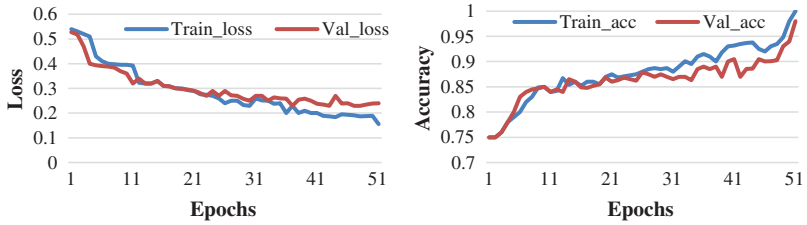

Figure 6: Accuracy and loss learning rate 0.001

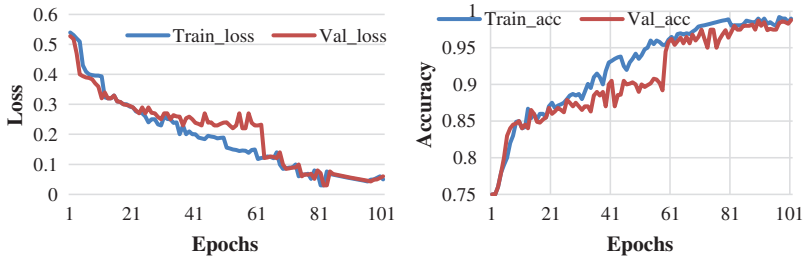

Figure 7: Accuracy and loss learning rate 0.001

Here, the experiment is conducted with 50 and 100 epochs size. "Fig. 8**:** shows the test with 50 epochs" and "Fig. 9**:** shows 100 epoch sizes with a learning rate of 0.01". Both show an accuracy rate that is 98.12.% and 98.12%.

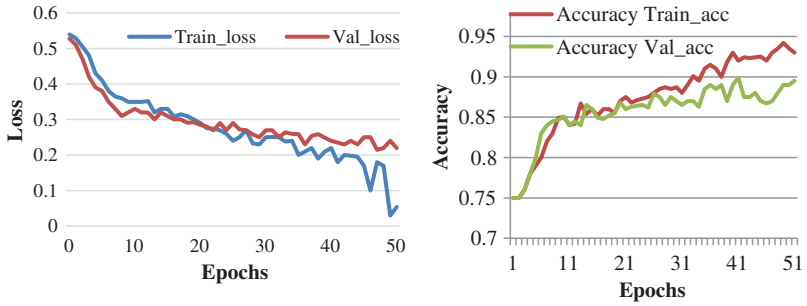

Figure 8: Accuracy and loss learning rate 0.01

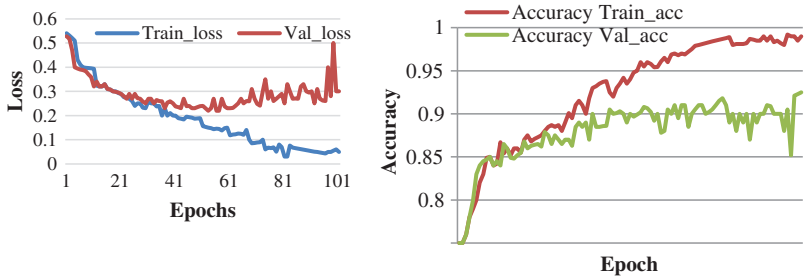

Figure 9: Accuracy and loss learning rate 0.01

Based on the assessment procedure performed, a more precise measurement of the data with a higher learning rate can be evaluated. "Tab. 4**"**: the result analysis based on the experiment".

Table 4: Experiment outcomes

Dataset size	Dimension	Epoch	LR	Accuracy (%)
2000	256 × 256 px	50	0.0001	98.02%.
		50	0.001	98.07%.
		50	0.01	98.12%.
		100	0.0001	98.00%
		100	0.001	98.25%
		100	0.01	98.12%.

Confusion matrix and linear distribution for proposed techniques is shown in "Fig. 10**"**:

The anticipated model is compared with other models and results are elaborated in Tabs. 5 and 6. The Tab. 4 and Fig. 11 describes the comparison of proposed model with other deep learning model. This shows that the proposed model has better accuracy then the other models. The space complexity of proposed approach is lowest among other models.

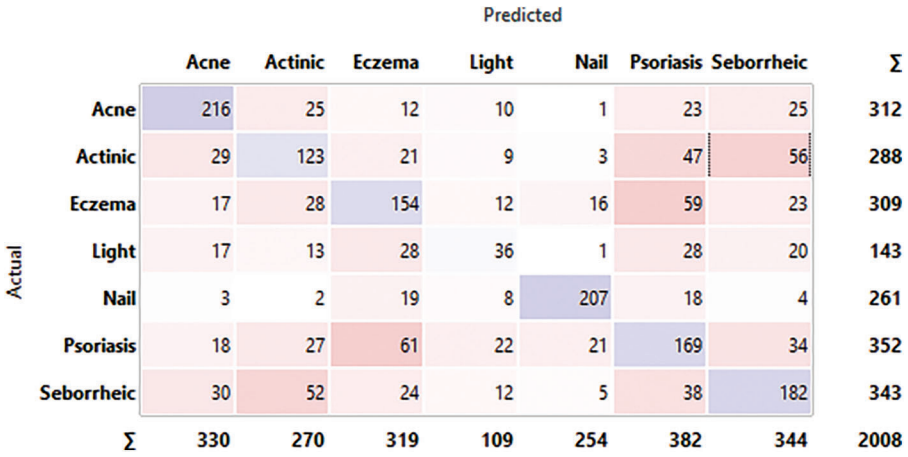

Figure 10: Confusion matrix

Table 5: Comparison with other models

Model	Accuracy rate	Space
Mobinet	70.46	82,566
VGG16	79.52	85245
InceptionV3	78.80	90255
Proposed	98	22565

Table 6: Comparison with other models

Model	Area under the ROC Curve(AUC)	Classification Accuracy(CA)	F1	Precision	Recall
kNN	0.786718	0.473108	0.456431	0.463252	0.473108
SVM	0.842799	0.539343	0.534904	0.540976	0.539343
Random forest	0.732663	0.420817	0.41342	0.41193	0.420817
AdaBoost	0.781722	0.468625	0.456797	0.459389	0.468625
Proposed	0.98	0.98	0.978	0.975	0.978

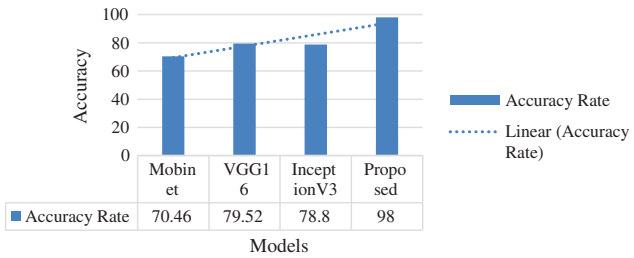

Figure 11: Proposed model comparison with state-of-the-art models

Tab. 6 and "Fig. 12" explains that the proposed model performs better than other models in terms of accuracy, F1-Score, Precision and Recall.

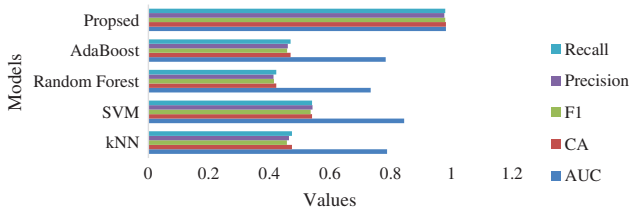

Figure 12: Proposed model comparison with state-of-the-art models

The conclusion and future work are described in Section 6.

6 Conclusion and Future Scope

In the past few years, skin disease is the reason for lots of casualties. The severity of skin disease is not possible to detect with naked eyes, therefore, requires a complex, costlier, and long process. Automated skin disease recognition acts a crucial role in diagnosis and reduces the death ratio. Therefore, AI-based techniques were developed to diagnose skin disease with maximum accuracy. This can help to reduce the spreading and expansion of skin disease. Still, skin doctors are facing issues with the accuracy of available techniques. The disease detection process should be mature enough to accurately identify or detect it. Here, in this paper, a skin disease detection system is proposed to accurately diagnose skin diseases. Image processing with a neural network helps to automatically screen and diagnose skin diseases at the preliminary stage. The approach used here is explained in different folds: firstly, the skin diseases images are pre-processed, and secondly, an important feature of the image is extracted. Thirdly, the pre-processed images are analyzed at different stages of the CNN model. The approach proposed in this paper is simple, fast, and shows accurate results up to 98% with different disease types. In the future, the plan is to develop a mobile application that takes input as skin images and provides complete details of disease based on the analysis.

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