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Deep Learning Based Detection of Dermatological Diseases Using Convolutional Neural Networks and Decision Trees

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ABSTRACT

The skin serves as a critical barrier that prevents germs from entering the human body. As such, skin infections are prevalent and can manifest in various forms, making the detection of skin diseases a challenging task. Traditional skin disease diagnosis is a complex process that relies on medical practitioners conducting a series of tests, which can be time-consuming and prone to error. Consequently, delayed or incorrect diagnoses can lead to extended testing periods, creating inconvenience for both medical practitioners and patients. Recently, there has been an increased interest in remote and automated diagnostic procedures. In response to this need, we propose a system for skin disease identification that combines image analysis and machine learning. The proposed method involves image normalization, application of the YCbCr color model, and the use of Convolutional Neural Networks (CNNs) and Decision Trees for disease detection. Our method has demonstrated successful identification of various skin diseases. In our experiments, it achieved precision, recall, and F-measure values of 74.76%, 74.76%, and 74.54% respectively. Thus, the proposed system offers a promising approach towards improving the efficiency and accuracy of skin disease diagnosis.

1. INTRODUCTION

Skin diseases represent a significant global health issue, impacting millions of people and contributing to substantial morbidity. The early and precise detection of dermatological conditions is pivotal to their effective management and the prevention of potential complications. Traditionally, dermatologists depend on their expertise and visual examinations to diagnose diverse skin conditions. However, this process can pose challenges due to the extensive variety of diseases and their often overlapping symptoms.

The advent of deep learning has brought about extraordinary successes in numerous medical image analysis tasks. Convolutional Neural Networks (CNNs), in particular, have transformed the realm of computer vision by autonomously learning distinguishing features from images. These networks demonstrate proficiency in detecting intricate patterns and have found successful applications in areas such as object recognition, image segmentation, and medical image analysis.

Our research is motivated by several factors. Firstly, manual diagnosis of skin diseases can be both time-consuming and subjective, with a potential for human error. Automating the detection process can enhance efficiency while providing uniform and unbiased assessments. Secondly, the growing availability of large-scale, annotated dermatological image datasets has opened the door to the application of deep learning techniques in this field. Lastly, advancements in computational power and the availability of pre-trained CNN models lay robust groundwork for developing accurate and powerful disease detection systems.

In this paper, we propose a deep learning-based methodology for the detection and classification of specific dermatological diseases, employing CNNs and Decision Trees. Our goal is to develop an automated system that can support dermatologists in diagnosing skin conditions accurately, using visual information derived from dermatological images.

To tackle the challenges inherent in dermatological disease detection, we harness the power of CNNs for feature extraction from dermatological images. CNNs can learn hierarchical representations by utilizing multiple layers of convolutions and pooling operations. These networks can capture both low-level features, such as edges and textures, and high-level semantic information present in the images.

Alongside CNNs, we employ Decision Trees for disease classification. Decision Trees offer an interpretable framework for mapping learned features to specific disease labels. By learning decision-making rules from training data, these trees can predict unseen images based on the extracted features.

We validate the proposed approach using a comprehensive dataset, comprised of a varied set of dermatological images annotated by expert dermatologists. Our experimental results underscore the effectiveness and potential of the proposed deep learning-based system in accurately detecting and classifying dermatological diseases.

2. LITERATURE SURVEY

Codella et al. [1] published a study that utilized deep learning ensembles for melanoma detection in dermoscopy images. Their system achieved a marked improvement in accuracy (76% as opposed to 70.5%) and specificity (62% instead of 59%) at a corresponding sensitivity level (82%). In a different study, Anantharaman et al. [2] concentrated on the development of a deep learning-based system named "Oro Vision" for classifying orofacial diseases. This work demonstrates how deep learning can be applied beyond traditional domains. Anthal et al. [3] employed an LVQ neural network to categorize vitiligo images into affected and non-affected areas. The authors demonstrated the potential of neural network techniques in automating the diagnosis of vitiligo, thereby offering a valuable tool for healthcare providers. Contrastingly, Rathod et al. [4] used image filtering techniques to eliminate unwanted noise from skin images, followed by image processing for enhancement. Their system achieved higher accuracy and faster results compared to traditional techniques. As such, their proposed system presents a more effective and reliable approach for the early detection of dermatological disorders. Harangi et al. [5] emphasized the detection of skin cancer using an ensemble of state-of-the-art deep learning methods. Their approach highlights the potential of combining multiple models to boost the accuracy and reliability of automated skin lesion diagnosis. Lastly, Hameed et al. [6] combined a deep convolutional neural network and an error-correcting output codes support vector machine. Their experiment, conducted on thousands of images sourced from diverse origins, achieved an overall accuracy of 86.21% using the ECOC SVM, showcasing another successful application of deep learning in medical image analysis.

Kondaveeti and Edupuganti [7] demonstrated that an enhanced ResNet50 structure could accurately identify skin abrasion images across seven different categories. With category-wise accuracy, weighted average precision, and recall rates of 90%, 0.89, and 0.90 respectively, this approach could serve as a clinical decision support system for dermatologists. Jin et al. [8] introduced a novel thresholding technique for detecting skin edges. While their approach could segment 58% of the dataset, a neural network was able to segment as much as 82%, indicating the potential superiority of deep learning methods. Rahi et al. [9] proposed a model based on the ResNet architecture, achieving an impressive accuracy of 90%. This result underlines the effectiveness of deep residual networks in dermatological image analysis. Rimi et al. [10] suggested a method that combines handling strategies with machine learning. By implementing this proposed methodology on dermnet images encompassing five hundred different diseases, the system achieved a precision rate of 73%. Rodrigues et al. [11] successfully classified various types of skin abrasions found in the International Skin Imaging Collaboration (ISIC) archive. Their approach achieved an impressive accuracy of 90%, showcasing the potential of deep learning in skin lesion classification tasks. Lastly, Junayed et al. [12] proposed an innovative deep CNN-based method capable of classifying five different types of eczema using an eczema-specific dataset. Through data augmentation, they improved the accuracy of image transformation. They also mitigated overfitting using batch normalization and dropout techniques, ultimately achieving an impressive accuracy of 96.2%.

Liao et al. [13] demonstrated that their proposed multi-label deep neural network surpasses traditional single-label classification methods in terms of robustness and accuracy. Their skin lesion characterization approach provides more detailed information about the attributes of a skin lesion, which can be valuable for clinicians in diagnosing and treating skin diseases. Agrawal and Aurelia [14] employed the Inception V3 model, which was initially pretrained and subsequently fine-tuned. This approach resulted in a significant increase in both training and testing accuracy. Although the authors clearly presented their methodology and experimental results, an in-depth analysis or discussion of the limitations and potential drawbacks of their approach was noticeably absent. In a comparative study, Borade and Kalbande [15] identified numerous skin ailments related to common skin problems as well as cosmetology. The authors highlighted the advantages of CNNs in capturing high-level features from medical images and provided examples of their applications in the detection and classification of skin lesions. They also discussed various algorithms, including support vector machines and k-nearest neighbors, detailing their respective strengths and weaknesses. Balasubramaniam [16] trained an Artificial Intelligence algorithm based on malignancy recognition using a deep ensemble and clinicians' contributions. Experimental results indicated that the proposed algorithm achieved high accuracy in melanoma classification, with the SVM classifier achieving an impressive accuracy of 95%, considered highly successful for melanoma diagnosis.

3. PROPOSED METHODOLOGY

CNN architecture in the proposed approach for the detection of dermatological diseases lies in its ability to effectively capture spatial features from images. CNNs have demonstrated outstanding performance in various computer vision tasks, including image classification and object recognition, making them a suitable choice for analyzing dermatological images. The architecture of a CNN is designed to exploit the hierarchical nature of visual data.

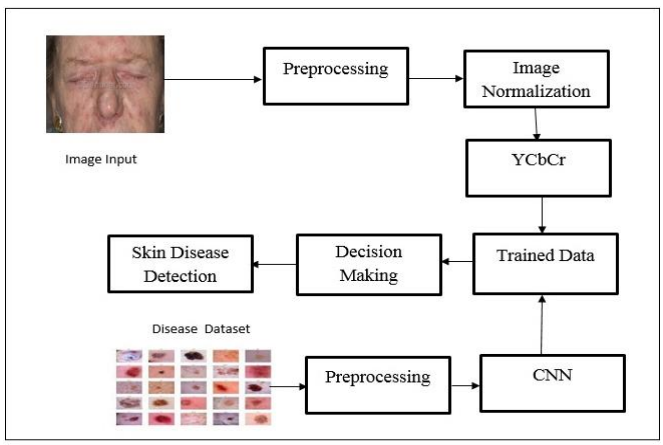

Figure 1. Proposed block diagram

This presented technique of dermatological disease identification is displayed in the Figure 1 above. The steps that are performed for achieving the presented approach is discussed in great detail in the succeeding section of this article.

Step 1: Dataset collection & Preprocessing – This is the first step of the presented skin disease detection approach.

Dataset Description – The skin disease dataset is collected from the URL [17]. The DermNet repository has thousands of images related to different types of dermatological diseases.

For the purpose of evaluation, a number of diseases are selected such as Actinic Keratosis Basal Cell Carcinoma consisting of 86 images, Hair Loss Alopecia consisting of 173 images, Eczema Photos consisting of 420 images, Nail Fungus and other Nail Disease consisting of 685 images, Melanoma Skin Cancer Nevi consisting of 141 images, Vascular Tumors consisting of 136 images, Acne and Rosacea consisting of 486 images, Exanthems and Drug Eruptions consisting of 173 images, Vasculitis consisting of 339 images, Urticaria Hives consisting of 181 images, Psoriasis Lichen Planus consisting of 343 images, Seborrheic Keratoses Tumors consisting of 77 images, and Warts Molluscum Viral Infections consisting of 495 images. This leads to a total number of 3735 images in the input skin disease dataset.

Preprocessing – For the preprocessing, the input skin disease images are resized to a size of 96×96 with color channel no. 3 which represents the RGB color model. The image needs to be converted into an array format which is accomplished by reading the images. These images are then labeled from 0 to 12 for the respective disease, 0 for Actinic Keratosis Basal Cell Carcinoma, 1 for Hair Loss Alopecia, 2 for Eczema Photos, 3 for Nail Fungus and other Nail Disease, 4 for Melanoma Skin Cancer Nevi, 5 for Vascular Tumors, 6 for Acne and Rosacea, 7 for Exanthems and Drug Eruptions, 8 for Vasculitis, 9 for Urticaria Hives, 10 for Psoriasis Lichen Planus, 11 for Seborrheic Keratoses Tumors and 12 for Warts Molluscum Viral Infections.

Number of Samples used to Train and Test – The images have been then splitted with a test size of 0.2 with random state at 42. This splits the input images into 80% training and 20% testing sets.

The training images are then further classified into 13 classes. The image data is then generated by these images through the use of various parameters such as, rotation range set at 25, width shift range set as 0.1, height shift range as 0.1, shear range as 0.2, zoom range at 0.2, horizontal flip is set as true and fill mode is initialized to nearest. This generated image dataset is then utilized in the next step by the convolutional neural networks.

Step 2: Training through CNN – In this stage, the image data procured in the previous step is used as an input for training a CNN for skin disease identification. The CNN model is first deployed successively, and the various layers are added as described in the Table 1.

The model initiates various layers for the evaluation of the gender. There are 5 convolution layers, the first layer consists of a kernel of size 3×3 and 32 in number. The padding is initialized as 'same' and the input shape is 96×96 which is the height and width of the image respectively. The ReLU activation function has given to this layer as given in the Eq. (1) given below. The channel dimensions have been used to achieve the batch normalization. A pool size of 3×3 is utilized for implementing the MaxPooling2D. A 25% dropout is applied to manage the output of the layers.

Table 1. CNN architecture

Layer Parameters	Activation Function
32×3×3 2D	ReLU
MaxPooling2D (3x3)	
Dropout (0.25)	
64×3×3 2D	ReLU
64×3×3 2D	ReLU
MaxPooling2D (3×3)	
Dropout (0.25)	
128×3×3 2D	ReLU
128×3×3 2D	ReLU
MaxPooling2D (2×2)	
Dropout (0.25)	
Flatten	
Dense (1024)	ReLU
Dropout (0.50)	
Dense (2)	Sigmoid

$$ReLU = max(x, 0) \tag{1}$$

Further 4 layers are employed in this fashion with variable kernel numbers which can be visually depicted in the Table 1 above. Along with these 5 convolution layers certain supplementary layers are added such as, the flatten layer to flatten the input along with a dense layer which has the parameters such as the ReLU activation function with the value as 1024. A dropout of 50% is applied to attain the batch normalization. This model is initiated for training purpose of 1000 epochs and a batch size of 64. This activation function being utilized is the sigmoid activation function as given in the Eq. (2) below. Once the model is trained, it is saved as an .h5 file in the prescribed location to be used for the testing purposes further. The CNN model can be accurately represented visually using the Table 1.

$$Sigmoid = \frac{1}{1 + e^{-x}} \tag{2}$$

Step 3: Testing – After the testing has been performed, the trained model is then loaded and the 13 classes are initialized. The test image is then provided to the methodology which needs to be normalized first before subjecting it for the evaluation. The image normalization procedure is effectively demonstrated in the section given below.

Image Normalization – The images provided for testing need to be normalized due to the fact that most of the images tend to have lower brightness which makes it difficult to understand the skin ailment. This procedure is achieved by the use of traversing the pixels one by one and extracting the R, G, B pixel values. These R, G and B values are then used to calculate the value of y as the yellowness or the brightness of the image. This is given by the Eq. (3) given below.

$$Y=(0.299*R)+(0.587*G)+(0.114*B) \tag{3}$$

This results in a value of y which is subject to classification of the pixel. If the value of y is greater than 200.65, then the R, G and B values are effectively added and a count is increased. This procedure is repeated for all the pixels in the image. The sum of all the selected R, G and B values are individually divided by the count obtained which gives us the mean Red, Green and Blue values. These values are further used to divide 255 which provides the multiplier values.

The obtained multiplier values are then used again on the input image to extract the pixel values are multiply them with

this achieved multiplier. This is done for all the pixels in the image and the resultant pixel values are evaluated for being greater than 255 which are then normalized to 255. These normalized values are set into the image which results in a brightness normalized image which is provided for the YCbCr color model evaluation. This procedure can be portrayed in following mentioned algorithm 1.

ALGORITHM 1: Multiplier value generation

```
// Input: MDR [mediaR], MDG [mediaG]
// Input: MDB [mediaB], SIMG[input image]
//Output: Multiplier values MR, MG, MB
// function: multipliervalueGeneration (MR, MG, MB, SIMG)
1: Start
2: CIMG = ∅
3:  for i = 0 to size of Width of SIMG
4:  for j=0 to size of Height of SIMG
5:    PSIGN = SIMG (ij) RGB
6:    R= (PSIGN >> 16 & HD)
7:    G= (PSIGN >> 8 & HD)
8:    B= (PSIGN >> 0 & HD)
9:    Y = 0.299 * R + 0.587 * G + 0.114 * B
10:   if(Y>200.65), then
11:   MDR= MDR+R, MDG= MDG+G, MDB= MDB+B
12:   end if, end for, end for
13: MDR=MDR/MDR.size, MDR= MDR/ MDR.size,
   MDR= MDR/ MDR.size
14:     MR= 255/ MDR, MR= 255/ MDR, MR= 255/ MDR
15: return MR, MG, MB
16: Stop
```

Skin Detection – The image normalized images are accepted in this step where the skin detection is performed. The skin detection is performed through the use of the YCbCr Model traverses the image in a pixel by pixel and extracts its RGB values. The RGB values are then used to achieve the Red Chroma and Blue Chroma component through the use of the Eq. (4) and Eq. (5) below:

$$Cb=-0.169*R-0.332*G+0.500*B+128 \quad (4)$$

$$Cr=0.500*R-0.419*G-0.081*B+128 \quad (5)$$

By using the Cb and Cr values yellowness in the image is estimated by using the Eq. (6):

$$t=Cb+0.6*Cr \quad (6)$$

These obtained values are then evaluated for their presence in the ranges given below.

$$Cr=137 \text{ to } 177$$
$$Cb=127 \text{ to } 77$$
$$\& \; t=190 \text{ to } 215$$

If the values of the particular pixel are in the above range, then this pixel is converted to white. If the pixels do not conform to the above ranges, then it is transformed into a black pixel. This is performed for all the pixels in the image, this leads to the effective conversion of the image into a binary image consisting of only white parts of the skin and the black parts as non-skin. This skin identified image is being subjected to the trained model for the purpose of decision making. The white pixels are then counted and this count is also provided to the next step.

Step 3: Decision Making – The testing module takes the image and the white pixel count as an input. If the count of the white pixels is more than 100 only the testing approach is initiated. Once the selected image contains more than 100 white pixels, the corresponding original image is extracted and preprocessed by resizing it to 96×96 and the image is cropped and provided to the trained model for the detection. The trained model analyzes the image and provides a label integer as an output. The corresponding class from the loaded 13 classes is identified based on the label integer and displayed to the user with a specific skin disease label.

4. RESULTS AND DISCUSSIONS

The approach mentioned in this article of research has been implemented using Python Programming Language to automatically detect the skin utilizing machine learning and image processing techniques. This is achieved through the employment of an Intel Core i5 CPU that is supported by 500GB of storage and 6GB of RAM, which is a typical configuration for a system. For development purpose the Spyder IDE is used along with the Keras and TensorFlow Libraries.

The performance metric has to be effectively evaluated to determine the efficacy of the proposed technique. This is done to ensure that the approach has been implemented successfully and determines the accuracy of the implementation. The deep learning methodologies are effectively uitlized for the purpose of skin detection need to be quantified to understand the performance improvement over the conventional approaches.

Performance Evaluation based on Precision, Recall and F Measure

Skin disease detection performance will be evaluated through extensive experimentation. The evaluation is based on the concept of the Precision, Recall and F Measure which evaluates accuracy value attained by the system. This is an accurate indicator that allows the determination of the level of absolute accuracy and the level of relative accuracy from the precision and recall respectively. The F Measure is a useful metric that combines these two metrics and achieves the overall accuracy of the execution. The equations utilized for the same are given in the Eq. (7) and Eq. (8) below:

$$Precision=A/(A+B) \quad (7)$$

$$Recall=A/(A+C) \quad (8)$$

$$F\ Measure=(2*Precision*Recall)/(Precision+Recall)$$

where, A=the number of accurate skin disease detected; B=the number of inaccurate skin disease detected; C=the number of accurate skin disease not detected.

For the experimental evaluation process, a set of 50 images for each category of disease, such as, Acne and Rosacea, Actinic keratosis Basal Cell Carcinoma, hair Loss Alopecia, Melanoma Skin Cancer Nevi, Nail Fungus, Seborrheic Keratoses Tumors, and Warts Molluscum Viral Infections. These images are then subjected to the entire procedure for the purpose of skin disease detection.

Table 2. Measurement of precision, recall and F measure

Skin Disease	No. of Test Images	No. of Accurate Skin Diseases Detected (A)	No. of Inaccurate Skin Diseases Detected (A)	No. of Accurate Skin Disease Not Detected (A)	Precision	Recall	F-Measure
Acne & Rosacea	50	40	10	10	80	80	80
Actinic Keratosis Basal Cell Carcinoma	50	30	20	20	60	60	60
Hair Loss Alopecia	50	50	00	10	100	83.33	90.909
Melanoma Skin Cancer Nevi	50	40	10	10	80	80	80
Nail Fungus & other nail Disease	50	30	20	20	60	60	60
Seborrheic Keratoses Tumors	50	50	10	00	83.33	100	90.909
Warts Molluscum Viral Infections	50	30	20	20	60	60	60

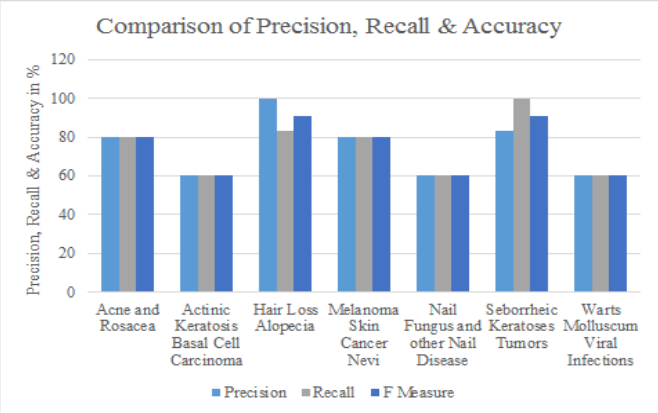

Figure 2. Evaluation of precision, recall and F measure

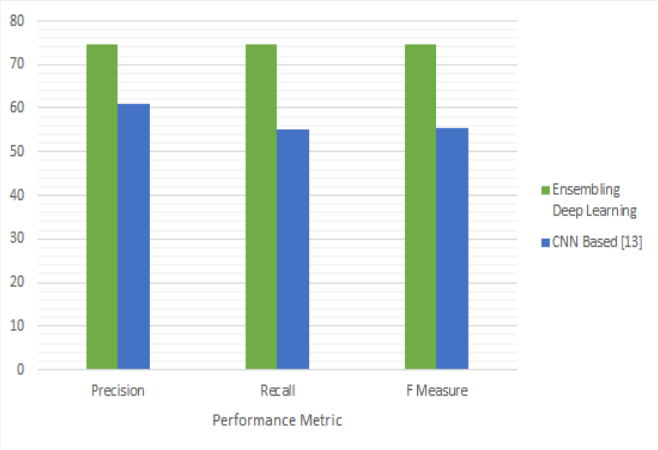

Figure 3. Precision, recall and F measure comparison with [13]

Table 3. Comparison of precision, recall, and F measure with [13]

Performance Metric	Ensembling Deep Learning	CNN Based [13]
Precision	74.76	61
Recall	74.76	55.15
F measure	74.54	55.5

The results of the Precision Recall and F Measure Table 2 are displayed in Figure 2 represents that the proposed methodology have impeccable accuracy. This is evident from the graph given above which achieves quite remarkable outcomes, such as Precision, recall and F Measure Values of 74.76%, 74.76%, and 74.54% respectively. The results have been compared to the approach defined in study [13] which also utilizes the CNN approach to specifically detect only one type of skin disease called skin lesions. The approach in study [13] has been contrasted with the presented technique, and the outcomes have been depicted in the Table 3. The comparison has also been detailed in the graph given by the Figure 3.

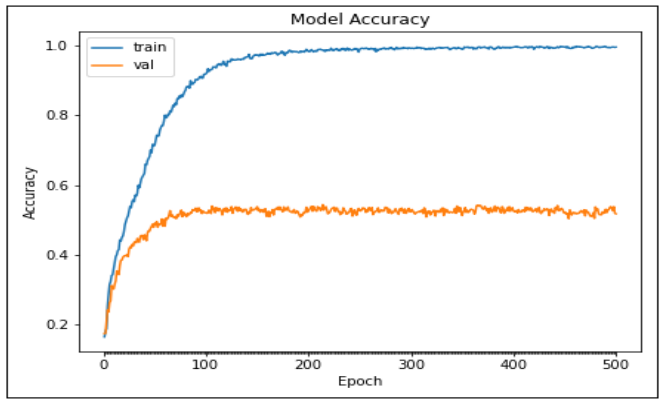

Figure 4. Model accuracy

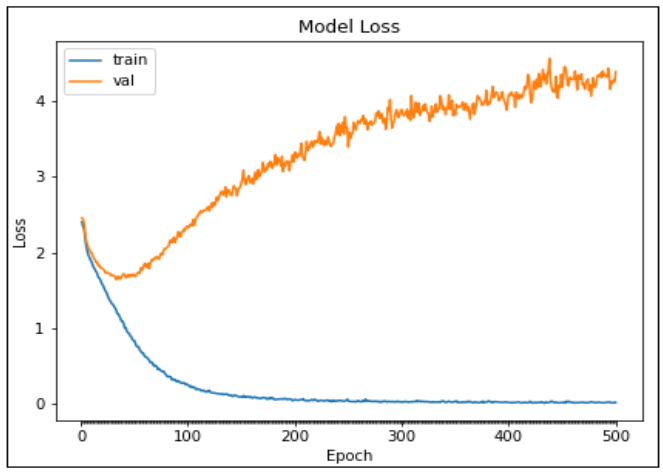

Figure 5. Model loss

As it is evident that the presented approach attains a considerably better precision, recall and F Measure scores in

comparison to study [13]. It is obtained as the presented technique is blend of effective image normalization and YCbCr color model to further enhance the deep learning paradigm.

This results in a breakthrough performance which is highly accurate for the purpose of identification of skin ailments through image processing use and deep learning. The model loss and model accuracy of the approach is plotted on a graph in the Figures 4 and 5.

5. CONCLUSIONS AND FUTURE SCOPE

The proposed methodology for automated skin disease identification has been developed substantially in this research article. The method obtains diseased skin picture as an input. The skin image is first preprocessed to resize the image as per the RGB color channel, the various disease images are thus selected and provided to train CNNs. The network is trained and a trained model file is achieved which can now be used for the purpose of testing. The testing image is provided to the system which is first resized and normalized. The image normalization approach enhances and optimizes the luminance levels to highlight the skin disorder. This normalized image is then provided to the YCbCr model which effectively detects the skin. This image is then provided to the trained model to identify the skin disease. Convolutional Neural Networks identify skin diseases, resulting in a probability score. These scores are sent into the Decision Tree method, which thoroughly categorizes the output and chooses the most appropriate illness based on the image. Experimentation was performed to determine technique performance, which yields Precision, recall and F Measure Values of 74.76%, 74.76%, and 74.54% respectively. Some of the limitations of proposed research work are such as Limited data availability, interpretability and class imbalance.

As a future research trajectory, a mobile application may be successfully created to allow the patient to capture an image of the ailment to achieve the automatic diagnosis on their smartphone.

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