



IJITCE

ISSN 2347- 3657

International Journal of Information Technology & Computer Engineering

www.ijitce.com



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AI BASED SYSTEM FOR DERMATOLOGICAL ILLNESSE' S PRELIMINARY IDENTIFICATION

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ABSTRACT

Skin disease among humans has been a common disease, millions of people are suffering from various kinds of skin diseases. Usually, these diseases have hidden dangers which lead to not only lack of self-confidence and psychological depression but also lead to a risk of skin cancer. Medical experts and high-level instruments are needed to diagnosis these skin diseases due to non-availability of visual resolution in skin disease images. The proposed framework includes deep learning techniques such as CNN architecture and three predefined models called Alex Net, ResNet, InceptionV3. A Dataset of images with seven diseases has been taken for the Classification of Skin diseases. They include diseases like Melanoma, Nevus, Seborrheic Keratosis etc. The dataset was extended by adding images having cuts and burns, which were classified as skin disease by most of the existing systems. The usage of Deep Learning algorithms has reduced the need for human labor, such as manual feature extraction and data reconstruction for classification purposes.

1. INTRODUCTION

Skin is one in every of the most important and quickest developing tissues of the human body. The burden of skin disease is regarded as a multidimensional concept that comprehends psychological, social and economic significance of the skin disease at the sufferers and their households and on society. It is a contamination that takes place in humans of all ages. Skin is regularly broken due to the fact it's far a touchy a part of the body. There are more than 3000 skin diseases. A cosmetically look spoiler disease will have a big effect and might reason extensive ache and everlasting injury. Most of the chronic skin conditions, along with atopic eczema, psoriasis, vitiligo and leg ulcers, aren't right now deadly, they may be diagnosed as an extensive problem on fitness popularity which include physical, emotional and economic outcome. On the other hand, skin cancers are potentially lethal and their trouble is associated with the temporality that they carry.

One of the most frequent ailments among people all over the world is skin disease. Basal cell carcinoma (BCC), melanoma, intraepithelial carcinoma, and squamous cell carcinoma are examples of skin cancers (SCC). The occurrence of skin cancer is currently greater than the occurrence of other new kinds of lung and breast cancer [1]. Several skin illnesses have symptoms that can take a long time to treat since they can grow for months before being recognized. As a result, computer-based disease diagnosis comes into play since it can produce a result in a short period of time with more accuracy than human analysis utilizing laboratory procedures. Deep Learning is the most widely used technology for skin disease prediction. Deep learning models will use inferred data to identify and explore features in unexposed data patterns, resulting in significant efficiency even with low computational models. This study presents a robust mechanism for accurately identifying skin diseases using supervisory approaches that reduce diagnostic costs. This has prompted the researchers to consider using a deep learning model to categorize the skin disease based on the image of the affected region. [2]

The following is how the rest of the article is Organized. Section 2 delves more into the related studies on recent technologies for detecting skin illness. The proposed strategy of classifying the type of skin illness using deep learning techniques is discussed in Section 3. The results and discussion are described in Section 4, followed by a conclusion and future work in Section 5.

2. Related Work

Manual diagnosis of skin diseases by visiting and consulting dermatologists is time consuming. Most rural areas do not have this option. These rural people need to travel to a nearby city for advice and diagnosis. This takes a lot of human effort. Not to mention, it costs a lot just to see your doctor. This also includes human contact, which is an unnecessary evil in this pandemic crisis. Few diseases are contagious. In the existing system, body contact is unavoidable. The existing computer-aided diagnosis involves identifying burns and injuries as skin diseases. The accuracy of these methods is not as good as needed. Thus, there is a need to develop a computer-aided system that automatically diagnoses the skin disease problem and differentiates skin diseases with other skin issues.

Quan Gan et.al [3] used image colour and Texture feature for the recognition of skin disease. Median filtering was used to pre-process the images. Denoise images are rotated to get the segments of the images. GLCM tool was used to extract text features and finally used SVM for classification of skin diseases herpes, dermatitis, and psoriasis.

Md Nafiul Alam et al [4]., “Automatic Detection and Severity Measurement of Eczema Using Image Processing”, suggested an automatic eczema detection and severity measurement model using image processing and computer algorithm. The system identified and determine the severity of eczema by allowing patients to input an image of the affected skin area. This system used image segmentation, feature extraction, and statistical classification to recognize and differentiate between mild and severe eczema. Once the eczema type was identified, a severity index was assigned to that image.

Later Researches used Deep learning techniques for classifying the skin diseases. Parvathaneni Naga Srinivasu et.al [5] used deep learning based MobileNet V2 and Long Short Term Memory for classifying skin diseases. A grey level co-occurrence matrix was used to estimate the progress of disease growth. The system has achieved an accuracy of 85% on the HAM10000 skin disease dataset. S.Malliga et.al [6], used the CNN algorithm for training and classifying all kind of clinical images. They have taken three types of skin diseases. They are Melanoma, Nevus, Seborrheic keratosis and achieved an accuracy of 71%. Nazia Hameed et.al [7] designed, implemented and tested to classify skin lesion image into one of five categories, i.e. healthy, acne, eczema, benign, or malignant melanoma using AlexNET, a pre-trained CNN model to extract the features. SVM classifier was used for classification and the overall accuracy achieved is 86.21%.

3. Dataset

A dataset of seven skin diseases was used in this study that includes Warts Mollusca, Systemic Disease, Seborrheic Keratosis, Nevus, Bullous, Actinic Keratosis, Acne and Rosacea. This dataset has over 7000 dermatoscopic images. The Dataset was expanded by adding new images (750), indicating skin burns and skin cuts. Existing systems have identified skin burns and skin cuts also as skin diseases. To Overcome this problem, the images representing cuts and burns were collected and added to the dataset. A random (rand) function is applied to split the data into the training data (5900) and validation data (1930).

4. Methodology

Proposed system is a web application that acts as a preliminary step for the diagnosis of a disease where a person uploads the image of the affected area of the skin and then gets to know the type of the disease and few suggestions are given regarding the disease using this application. The proposed framework involves a deep learning-based method to detect skin diseases. This system will utilize computational techniques to analyse, process, and relegate the image data predicated on various features of the images. The Architecture of skin disease detection and classification system

is shown in the following figure 1.

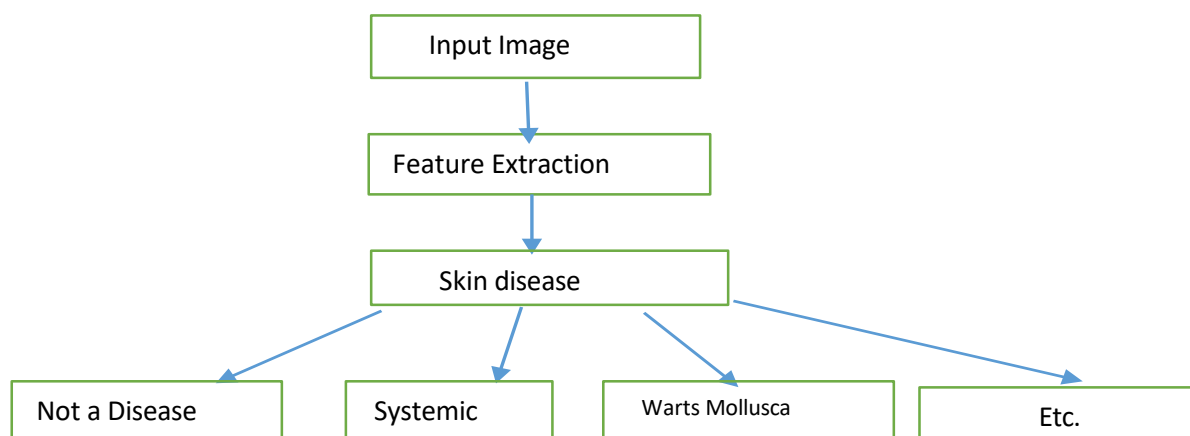


Fig 1. Architecture of Detection and classification of Skin Diseases

4.1 Deep Neural Network Architectures

4.1.1 CNN architecture

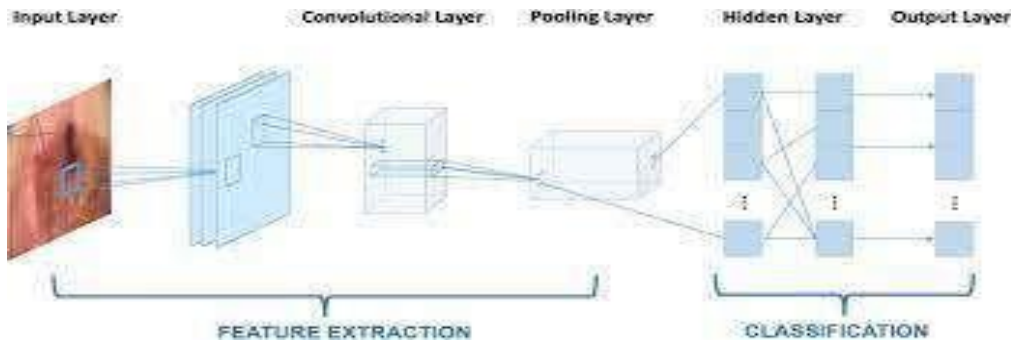


Fig.2. CNN Architecture

The Convolutional neural network shown in figure 2 consists of an input layer, hidden layers and an output layer. In any feed-forward neural network, middle layers are called hidden because their inputs and outputs are masked by the activation function and final convolution. In a convolutional neural network, the hidden layers include layers that perform convolutions. This product is usually the Frobenius inner product, and its activation function is commonly ReLU. As the convolution kernel slides along the input matrix for the layer, the convolution operation generates a feature map, which in turn contributes to the input of the next layer. This is followed by other layers such as pooling layers, fully connected layers, and normalization layers. Convolutional layers convolve the input and pass its result to the next layer. Pooling layers reduce the dimensions of data by combining the outputs of neuron clusters at one layer into a single neuron in the next layer. Fully connected layers connect every neuron in one layer to every neuron in another layer [8].

4.1.2 ResNet152V2

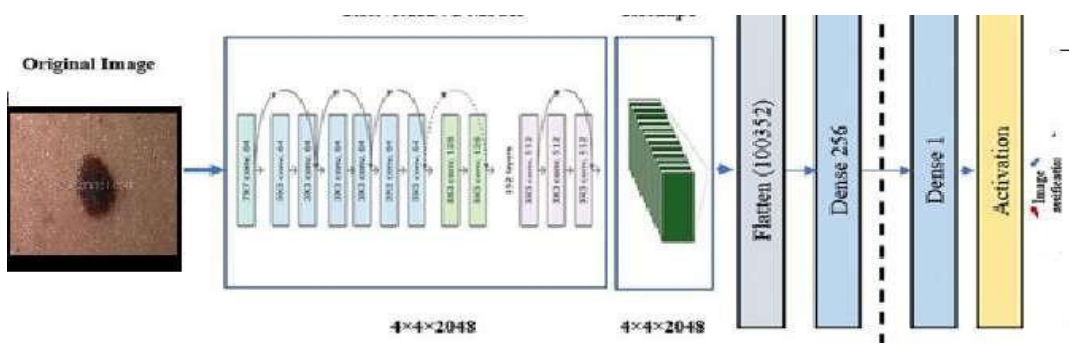


Fig.3 ResNet152V2 Architecture

The architecture of ResNet152V2 is shown in figure 3. It is used as a feature extraction model which is trained on imageNet dataset. The model has initial weights because it is a pre-trained model, which can help to gain acceptable accuracy faster than a traditional CNN. The model architecture consists of the ResNet152V2 model followed by a reshape layer, a flatten layer, a dense layer with 128 neurons, a dropout layer, and finally a dense layer with Softmax activation function to classify the image into its corresponding class. Resnet introduces a structure called residual learning unit to alleviate the degradation of deep neural networks[9]. This unit's structure is a feedforward network with a shortcut connection which adds new inputs into the network and generates new outputs. The main merit of this unit is that it produces better classification accuracy without increasing the complexity of the model.

4.1.3 AlexNet

AlexNet is the name of a convolutional neural network which has had a large impact on the field of machine learning, specifically in the application of deep learning to machine vision. It is attached with ReLU activations after every convolutional and fully-connected layer.

As shown in figure 4, the Alexnet has eight layers with learnable parameters. The model consists of five layers with a combination of max pooling followed by 3 fully connected layers and used Relu activation in each of these layers except the output layer.

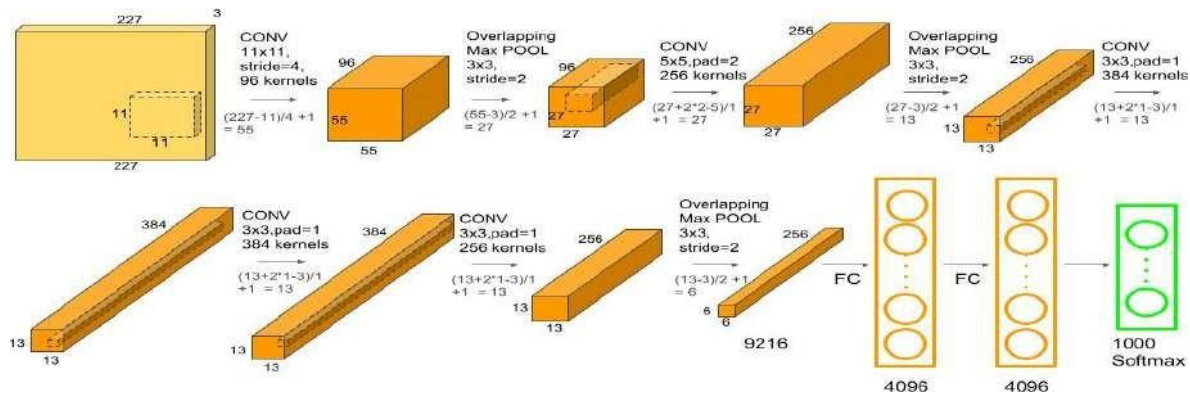


Fig. 4 Alexnet Architecture

The input to the Model is RGB images. It accelerates the speed by 6 times at the same accuracy. It used two Dropout layers. The activation function used in the output layer is Softmax. The total number of parameters in this architecture is 62.3 million [10].

4.1.4 Inception-v3

As shown in the figure 5, Inception v3 is a pretrained model which was originally trained on ImageNet dataset which has over a million images from 1,000 classes on some very powerful machines. Being able to retrain the final layer means that you can maintain the knowledge that the model had learned during its original training and apply it to your smaller dataset, resulting in highly accurate classifications without the need for extensive training and computational power [11].

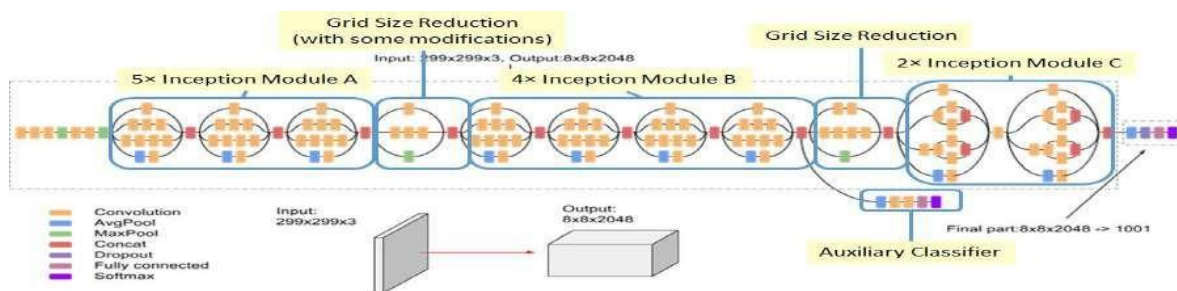


Fig.5. Inception-v3

5. Results and Discussions

The proposed system is to classify the given skin image as 'Not a Skin disease' or one of the seven diseases namely Warts Molluscum, Systemic Disease, Seborrheic Keratosis, Nevus, Bullous, Actinic Keratosis, Acne and Rosacea using deep learning techniques. The dataset is divided into training and testing and deep learning models are build using CNN and three pretrained networks called Alex Net, ResNet, InceptionV3. The train and test accuracies of different models are shown in Table 1.

Table 1: Models Train and Test Accuracies

Model	No. of epoch's	Training Accuracy	Test Accuracy
CNN	40	99	33.49
RESNET152V2	40	88.83	64.62
INCEPTION V3	45	65.46	61.23
ALEXNET	45	74.89	58.32

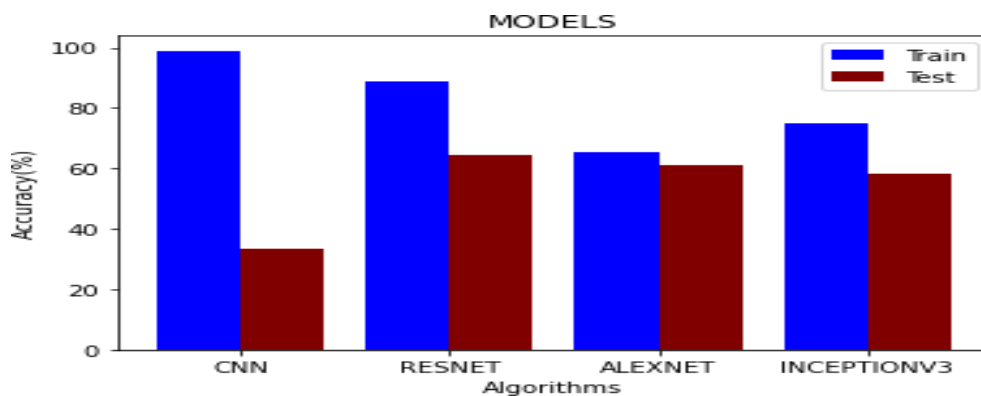


Fig.6 Performance of Deep neural networks

The train and test accuracies of CNN, Resnet, Alexnet and Inception-v3 are also shown in the bar graph (Fig.6). From the graph it is observed that CNN has outperformed over training Data but not on test data so it has lead to overfitting of the model. Resnet Train and test accuracies are better compared to the other models. So Resnet architecture can be used for detecting and prediction of skin diseases.

Some of the results of our experiment are shown in Fig. 7. A new image can be given as input through our UI. The system detects whether it is skin disease or not. if disease classifies it into one of the seven diseases. highlights the effected portion of the skin and shows some tips as primary treatment.

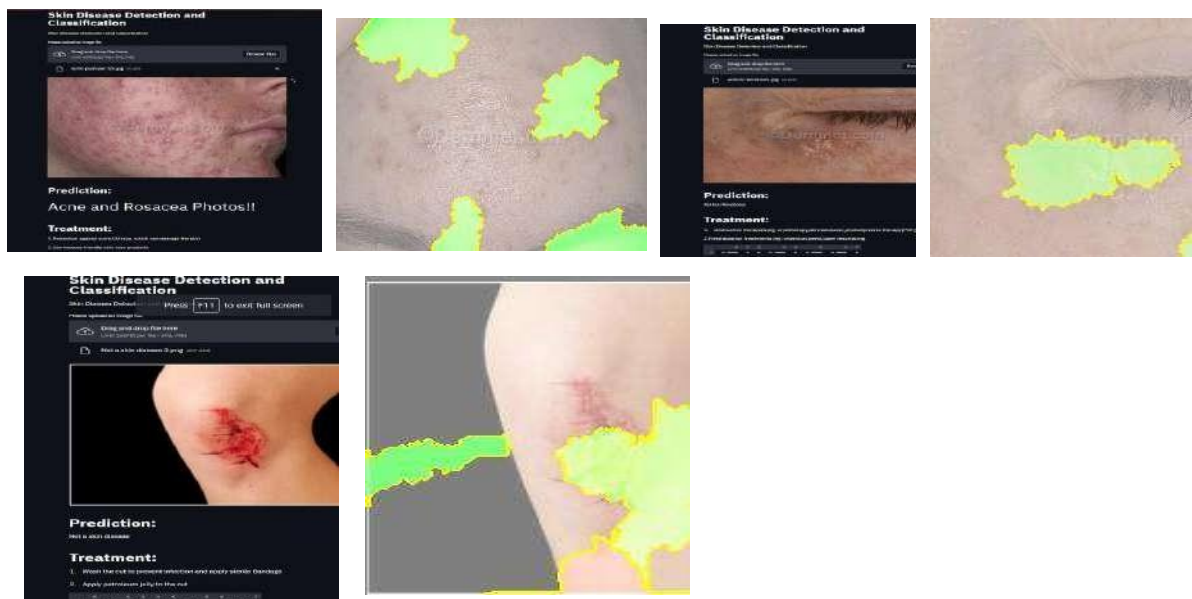


Fig.7 Diagnosis Results

6. CONCLUSION

The feasibility of building a universal skin disease classification system has been investigated using CNN, Resnet, Alexnet and Inceptionv3. CNN has outperformed over training data but not on testing data. Better accuracy can be obtained by providing a training set with more variance and also by increasing its size. It is also found that Resnet has given better accuracy compared to other networks in the diagnosis of skin diseases.

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