Medical Image Analysis For Detection And Prediction Of Skin Diseases Using CNN

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Abstract
Skin disease is one of the most unpredictable and common diseases in our country. It is caused by bacteria, allergies, viruses, fungal infections, etc. Since skin diseases are common and the patients are in large numbers, medical care is required and it should not be ignored. It is very difficult to detect and diagnose due to its complexity. With the advancement in technology, it is conceivable to identify the type and intensity of skin diseases accurately. In dermatology, for finding the condition of the skin, expensive investigations have to be carried out for the diagnosis of the disease. This paper proposes a technique that utilizes analysis of images that extracts the maximum information required for diagnosis by utilizing appropriate data. They are the position or location of disease and segmentations at deformities, or by utilizing the assessable features of appearance indicators from image. A decision system that utilizes manifold classifiers similar to the feature-based neural networks technique is used. Based on the classifier output weight the final decision system is designed. Classification can be improved for better diagnosis based on calculated accuracy for better decisions.

Keywords: - Transform learning, Resnet, Densnet, Inception, CNN.

I INTRODUCTION

Skin is the prime organ and authoritative defense organ of the human body. Its main action is to shield and protect the internal organs of the body from damage. Since skin is an external organ, it can also yield to factors like genetic or external environment that skin tends to be constantly influenced. Generally, skin is affected by severe impurities caused by dust, viruses, or fungus. Skin also acts to elude the loss of lipids along with water from the layer of the dermis and epidermis subsequently barrier function of the skin is stabilized. Generally, three chief kinds of skin diseases can be seen in the human body, such as fungal, viral and allergic diseases. Even though these diseases can be cured easily if diagnosed properly, else can lead to trouble in the life of the patient, if not treated. The majority of the conclusion about skin disease is based on the existing symptom that is drawn based on the experience of the subjective doctor. This may lead to negative conclusions if not properly diagnosed and may lead to delay in treatment. For these purposes, excessive hypothetical consequences and practical assessment are used to learn exactly how to extract indications of varied skin diseases by utilizing modern technology. To decrease the spread and growth of skin diseases, it has to be diagnosed in the primary stage properly. It requires the physical presence of the patient and an experienced physician for diagnosis as well as treatment, which consumes more time as well as it is expensive. The type and stage of the disease cannot be easily predicted by common people, since common itching or sometimes symptoms may be ducted after a long time. Its impact on a problem may cause severe damage to the skin with further growth. At times, even a dermatologist may find it tough to identify the type of infection and might involve costly laboratory investigations to appropriately recognize the stage as well as the type of infected skin disease.

Using current Machine Learning and Deep Learning advancements, it is possible to detect and predict skin cancer much more quickly and accurately. Thus, making it a reliable and cost-effective solution. Detection of skin diseases by utilizing image processing-based techniques has been utilized by many researchers. Classification of color images using clustering based on K means and ANN is utilized to categorize its type [1], in this algorithm image algorithm is used to identify the disorder with better accuracy, and the prototype system model of skin disease is created to detect a lesion in the medical image by analyzing texture based on neural network and thresholding. This technique is used to diagnose skin disease using medical images. The convolution layer is used for classification that utilizes a learning rate for good accuracy for the detection of four types of skin diseases [2]. Skin lesion based on pigmentation is used to detect the disease which is useful for face images [3]. This paper is used combines a CNN as well as self-organizing mapping to classify images. Automated techniques used for the diagnosis of common skin disease uses deep learning technique that acquires images from a smartphone and is used for pre-processing and improved technique to detect skin diseases [4]. MobileNet V2 and LSTM-based technique provides efficient classification and detection of skin disease for real-time application [5].

An application based on mobile can be useful for proper and instant action and also helps dermatologist to detect disease at its initial stages. Skin disease detection without doctor intervention by utilizing images consists of two stages, utilizing color images of infected skin by using k means clustering that is used to recognize the disease, and using artificial neural network classification of disease is utilized [6]. This proposed algorithm is used to test six types of disease with better accuracy. Numerous machine learning algorithms have confirmed a better result with better efficiency to detect skin disease at different stages of the lesions. Grouping of diseases is very hard to diagnose in the case of images due to dissimilarity in their shapes and types of disease. Some of the prediction techniques depend on digging up a set by utilizing clinical features and histopathological physical appearance to describe disease [7]. Skin disease indications are long-lasting and unceasingly varying processes, for this reason, patient diagnosing under this complaint needs to be provided with a valuation for the extent of time from the occurrence of first lesions. Some of the patients are unaware of the high risks that may cause to the skin due to the complex varying circumstances.

A real-time and unique method based on artificial intelligence technique that utilizes a self-learning and statistics conception can be used to provide medical care [8,9]. In the healthcare industry, an efficient system with a better accuracy-based classifier must be developed that predicts the category of disease, with minimum conflict for different diseases. These results must be utilized by the doctor as a second option to avoid harming the patient's safety [10]. Recent technology like the Internet of Things has added significantly to the expansion of diagnosis as well as detection in medical systems. Physicians are now utilizing this technique in various fields of medicine for patient diagnostic ability that can be augmented without disturbing patients physically [11]. For this purpose, smart methods have been developed by professionals to diagnose different types of diseases accurately. Even though there is a problem of managing data of discrepancy among rare diseases as well as common diseases remained an exposed problem to be solved even today [12]. Neural network and thresholding methods are used to detect skin lesions of the input image that detect the texture of the image [13]. Prediction of presence and absence of disease based on input image using Android application. It is also used to train and suggest diagnosis techniques like medical drugs as well as recommend medicinal explanations as well as surgery for doctor advice. Since it's a queries based interaction it may lead to misinterpretation of data [14]. Matlab-based detection of some of the common types of skin disease by extraction of features in images. This system even alerts the physicians if any abnormalities are detected. The major disadvantage of this system is the accuracy of classification as well as segmentation issues [15]. Matlab toolbox is used to process skin allergies by utilizing data mining methods and image processing techniques for a given set of image datasets [16]. An appropriate diagnosis of the consequence will lead to correct medication that can minimize the end effect on the people suffering which can lead to generating awareness. A suitable prototype has been developed by utilizing a neural network to detect skin diseases. A better precision can be achieved by actualizing our framework on the dormant dataset that is utilizing different images of diseases of 500 datasets.

This article is organized as follows, Section 2 provides the background and the methodology of implementation for the detection of skin disease Whereas Section 4 provides and evaluates the results and Section 5 concludes this paper.

II METHODOLOGY

The approach required for the detection of skin diseases can be used for extraction of information, recognition of skin disease, as well as classification, employing image-based systems. This proposed scheme will assist doctors in meaningfully detecting some of the skin diseases like melanoma, Eczema and Psoriasis. Fig 1 describes the general approach for the detection of skin disease by using the CNN technique and image processing. In the present proposed approach, the skin images are dealt with by using image processing. This skin-diseased image is processed using pre-processing, feature extraction and classifier using machine learning to predict skin diseases that are required for medicinal guidance. This algorithm is successfully used to forecast whether skin disease is present or not. In the data processing stage, the image processing phase involves pre-processing, segmentation, and feature extraction steps. The machine learning stage involves processing, training and detection steps. The correlation values obtained from the input skin image are utilized by the classifier model. The convolutional neural network is used for classification of input data. This model identifies Psoriasis, Lichen Planus, and Pityriasis Rosea as some of the skin diseases. A neural network is incorporated to provide results with better accuracy.

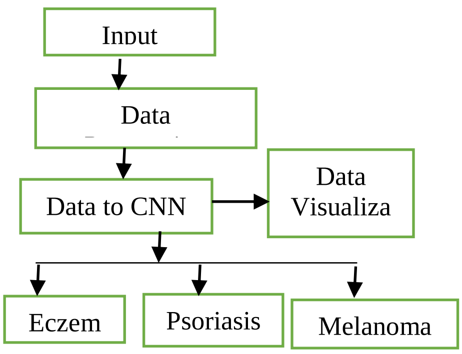

Fig 1 Proposed algorithm for skin disease detection

A. Transfer Learning

One of the machine learning techniques is transfer learning, this model is established aimed at a mission and is used again as the initial point for the next task. The input dataset contains images of skin lesion detail of about 4,000 images obtained from different websites. Preparing our dataset for training involves assigning paths and labeling the images followed by dividing the data into training, authentication and trial data. The pre-trained model is fine-tuned by adding and deleting a few layers, freezing and training a few layers, and adding the top layer and output layer according to our classes. Data is trained on a fine-tuned network. This algorithm is implemented by taking the data set for our project from Dermnet. Around 4000 images were collected of diseases- eczema, Melanoma and psoriasis from it. This data set is loaded and resized the images and labeled the data for the diseases. Then, the dataset is concatenated to join the arrays of the same shape along a specified axis, which is then trained and validated data. This data is then converted to the class vector to a class matrix of size 3 since we need to classify a three-class problem. They implemented four techniques like inception V3, VGG 16, resnet 50 and densenet. The input images are shaped to 224 x 224 and the weights are loaded from an image. These weights transform the input data within the network's hidden layers. If the layers had the attributes moving-mean, variance, and updated them and batch normalization is performed. Batch normalization normalizes the data to a layer for individual mini-batch. It also reduces the number of training times required in training deep networks. Adam optimizer is used since it provides an optimization algorithm that can handle noisy problems. Categorical cross-entropy is a loss function because it can be used for a multi-class classification task and the model can take a decision when a particular image can belong to one out of many possible categories. Later fine-tuning was performed. Subsequently, the input data aimed at the neural network is analogous to the deep learning technique, it befits comparatively easier to program the new module. In the first stage, information is imported from the current comparable deep learning model, ant then the model has existing connections, this can be made as a trainable layer as false and observed how the model behaves and then added and deleted layers conditional upon the similarities of the two models and trained the model. Once input is added/ removed the layers depend upon the data required, at this stage new model is frozen, i.e., the layer does not require any modification to the data delimited in them. Updating the weights has to be is by training the new model through the new task as well as data. The final stage is to train the input model on the test information. These layers were modified and trained using a deep network that can recognize the disease. The average layer weights of others will remain the same till the new model is trained. Then, training of the output layer is used for displaying the results intended for deep neural networks. The result of each model such as training accuracy, validation accuracy, test accuracy and confusion matrix is generated.

B. VGG16

VGG16 is fine-tuned to form top fully-connected layers containing: one inclusive maximum pooling layer, one entirely connected layer through 1072 units, one dropout layer with 0.2 rates, one softmax initiation layer for 3 types of skin lesions, and by adding one classification tasks. Initially, restrict all layers in VGG16, and can achieve feature extraction for the recently added fully connected layers, for this purpose layer weights are not completely arbitrary and the slope may not be moreover higher values for fine-tuning the values. Subsequently, by unfreezing the feature extraction values, the final convolutional block of VGG16 and the model begins with initial fine-tune values. Optimizer like Adam is utilized for the training process, learning rate of 0.0001.

C. Inception V3

Inception V3 is a 48-layer CNN algorithm with the highest performers arranged on ImageNet through 0.937 and 0.779 for top-5 and top-1 respectively. Inception V3 used to basically for small models inside a larger model. Fine-tune the different stages of Inception V3 including the top 2 fine-tune layer is standardization layers in the model set to trainable.

D. Resnet 50

Resnet50 can be fine-tuned by removing the best fully-connected layers, and new layers can be implemented by levels the previous layer of a pre-trained and advanced layer is associated to condensed layer with rely on initiation task trailed by a removing layer with 0.5 rates, one softmax initiation layer for all three different types of skin diseases, that classification tasks. Primary, freeze all layers and complete feature extraction so that again added fully connected layers to fine-tune the layer by discarding larger values of the gradient. Final convolution blocks are unfreezing after feature extraction and begin with a new fine-tune model. An optimizer such as Adam is used to train the process training since the learning rate is 0.0001 and the cross entropy function is minimum.

E. DenseNet

Dense Net 201 has 4 dense blocks. In the case of a dense block, inputs are in the first layer, which comprises feature maps of all earlier convolutional blocks as well as its feature maps that are passed on to all L-1 layers succeeding. The individual layer accepts the states from its previous layers and inscribes them to the succeeding layers. It not only updates its state but also updates the data information that desires to be stored. The architecture of DenseNet distinguishes between information that is updated to the network and data that is stored by concatenating structures in its place of summing features as in ResNet. In the condensed block, each layer produces feature maps from a complex function through successive procedures, such as standardization of batch, ReLU, and convolution. Pooling as well as convolution layers of each dense block is known as a transition layer. DenseNet201 comprises four dense blocks. Fine-tuning of DenseNet201 uses the same procedural training strategy as in previous sections of Dense Net. The top layers were fine-tuned for 27 epochs for DenseNet, while 20 epochs were required for fine-tuning DenseNet 20.

IV RESULTS AND DISCUSSION

After the training model with the CNN module, the assessment of this training module is the subsequent process. The training module is asses to check its validation and process. A statistical method for assessing and relating the learning algorithm is implemented. Data training, as well as validation, are cross-validated for multiple epochs. For every iteration first fold has L-1 data to study individual models, and the following simulations are trained with data to make predictions. By using the confusion matrix and its accuracy the performance of all training algorithm are calculated.

VGG16 Results

Initially, data is trained on a pre-trained model by freezing all the layers(blue) in which around 72% of accuracy is reached, then we made 5 layers as trainable(green) to improve the accuracy slightly, after which we trained only 4 layers(yellow), followed by training 6 layers(red) which lifted the accuracy to around 80%. Figure 2 shows the accuracy and loss of the VGG16 algorithm

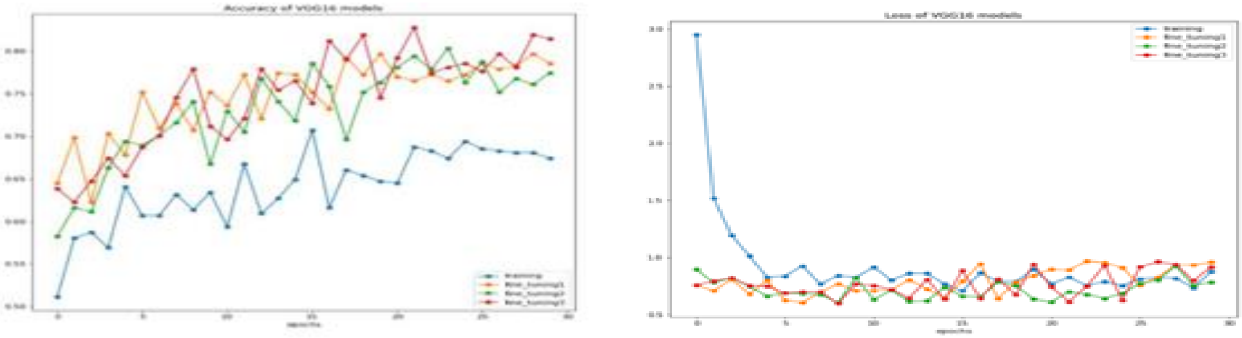

Fig 2 Accuracy and Loss of VGG16 algorithm

Inception V3 Results

Initially, data is trained on the pre-trained model by freezing all the layers(blue line) in which around 69.5% of accuracy is reached, then we made the last convolution block of layers trainable(red) to improve the accuracy slightly, after which we trained only last few layers(green), followed by training layers from 251 to 311(yellow) which lifted the accuracy to around 81.65%. Figure 3 shows the accuracy and loss of the Inception V3 algorithm

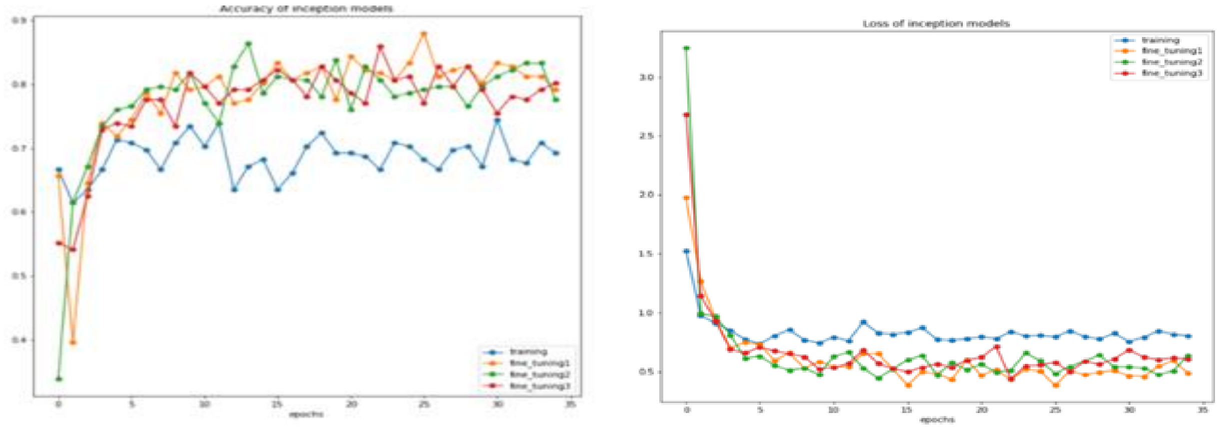

Fig 3 Accuracy and loss of Inception V3 algorithm

Resnet 50 Results

Initially, data is trained on a pre-trained model by freezing all the layers(blue line) in which around 72% of accuracy is reached, then we made the middle 5 layers trainable(green) to improve the accuracy slightly, after which we trained only last few layers(yellow), followed by training first 6 layers(red) which lifted the accuracy to around 80%. Figure 4 shows at accuracy and loss of the Resnet 50 algorithm

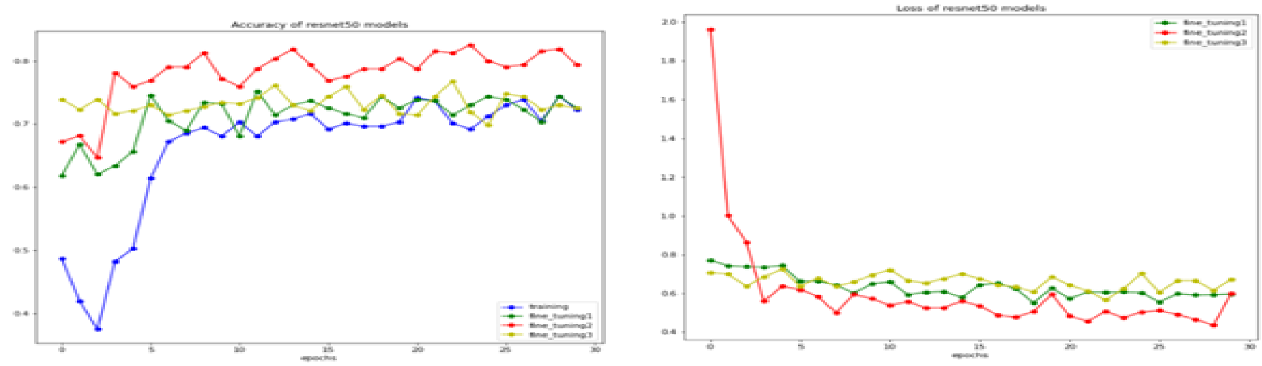

Fig 4 Accuracy and loss of Resnet algorithm

DenseNet Results

Initially, data is trained on a pre-trained model by freezing all the layers(blue line) in which around 74.3% of accuracy is reached, then we made the middle 5 layers trainable(green) to improve the accuracy slightly, after which we trained only the last few layers(yellow), followed by training layers from 481 to 511(red) which lifted the accuracy to around 81.7%. Figure 5 shows the accuracy and loss of the DensNet algorithm.

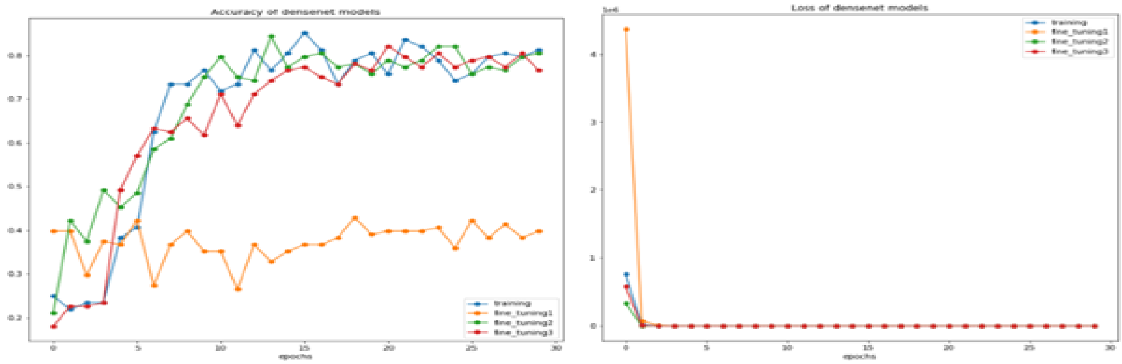

Fig 5 Accuracy and loss of DensNet algorithm

Comparison of Results

The best models from each architecture are selected based on their accuracy and loss on the test set and validation set, and also by evaluating their performance on a test set i.e., by checking the number of correct and incorrect predictions. Table 1 shows the performance analysis of different algorithms used in this article

Table 1 Performance analysis of different algorithms.

Model	Validation Accuracy	Test Accuracy	**Test loss**
VGG16	81.47%	81.97%	0.56
INCEPTION V3	81.65%	87.21%	0.399
RESNET50	72.54%	73.8%	0.58
DENSENET	78.24%	81.7%	0.57

V CONCLUSION

Detection of skin disease is by using four types of CNN models that were trained on pre-trained models that is vgg16, inception V3, Resnet50 and Dense Net. This is done by using Transfer Learning and were able to achieve a good accuracy of results for the prediction and classification of skin diseases (eczema, melanoma and psoriasis). Models are trained in such a way that they avoid overfitting & provide a generalized output. VGG16 as well as Inception V3 has shown a better validation accuracy of more than 81% but Inception V3 has provided a food test accuracy as well as test loss with can be seen in Table 1. Skin diseases have a distinguishing characteristic in the data obtained from the image that will be at ease in the interpretation of some diseases but not for all skin diseases. Based on the outcomes of the result for the detection of skin diseases based on the CNN model can be used for the skin disease classification system.

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