Diagnosis of Skin Diseases Using Modified Convolutional Neural Networks

Dr. A. Sumaiya Begum[1], Keerthana. S[2], Pooja. V[3], Priyadarshini. M[4]
[1]*M.E, PhD, Associate Professor, Department of Electronics and Communication Engineering, R.M.D Engineering College, Anna University (affiliated) Chennai, Tamil Nadu, India*
[2,3,4] *IV Year UG Students, Department of Electronics and Communication Engineering, R.M.D Engineering College, Anna University (affiliated) Chennai, Tamil Nadu, India*

***Abstract*- Dermatology is one of the most unpredictable and difficult terrains to diagnose due to its complexity. In the field of dermatology, many a times extensive tests are to be carried out so as to decide upon the skin condition the patient may be facing. The Time may vary from practitioner to practitioner. This is also based on the experience of that person too. So, there is a need of a system which can diagnose the skin diseases without any of the constraints. We propose an automated image based system for recognition of skin diseases using machine learning classification. This system will utilize computational technique to analyse, process and relegate the image data predicated on various features of the images. Skin images are filtered to remove unwanted noise and also process it for enhancement of the images. Feature extraction using complex techniques such as Convolutional Neural Network (CNN),classify the image based on the algorithm of logical regression and obtain the diagnosis report as an output. This system will give more accuracy and will generate results faster than the traditional methods, making this application an efficient an dependable system for dermatological diseases detection. Furthermore, this can also be used as a reliable real time teaching tool for medical students in the dermatology stream.**

***Index terms*- Convolution, feature extraction, Medical Image Processing, Machine Learning classification, Dermatology, Image processing, Deep learning, Computational Intelligence, Automated Diseases Diagnosis**

I.INTRODUCTION

The Dermatology remains the most uncertain and complicated branch of science because of it complicacy in the procedures involved in diagnosis of diseases related to hair, skin and nails. The variation in these diseases can be seen because of many environmental, geographical factor variations. Human skin is considered the most uncertain and troublesome terrains due to the existence of hair, its deviations in tone and other mitigating factors. The Skin diseases diagnosis includes series of pathological laboratory tests for the identification of the correct diseases. For the past ten years these diseases have been the matter of concern as their sudden arrival and their complexities have increased the life risks. These skin abnormalities are very infectious and need to be treated at earlier stages to avoid it from spreading. Total wellbeing including physical and mental health is also affected adversely. Many of these skin abnormalities are very fatal particularly if not treated at an initial stage. Human mindset tends to presume that most skin abnormalities are not as fatal as described thereby applying their own curing methods. However, if these remedies are not apt for that selective skin problem then it makes it even worse. The available diagnosis procedure consists of long laboratory procedures but this paper proposes a system which will enable users to predict the skin diseases using computer vision.

II. RELATED WORKS

Many studies have applied deep learning algorithms to skin diseases. For example, the performance in the task of classifying skin tumors using the Inception-v3 network has reached the level of professional dermatologists; for nine classes of tumors, a computer achieved an accuracy of 55.4%, and two dermatologists achieved accuracies of 53.3% and 55.0%. Using the same network structure, achieved an accuracy of 87.25 ± 2.24% on the dermoscopic images for four common skin diseases, including SK,

BCC, psoriasis and melanocytic nevus. These studies show that current deep learning methods have the potential to be applied to dermatoses.

At the same time, the application of deep learning to face related diseases is also promising. Reference designed a deep learning algorithm called DeepGestalt and trained their model on more than 17,000 real facial images of genetic syndromes and this model can identify more than 200genetic syndromes using facial images with relatively high precision. Reference investigated using CNNs to classify acne into different severity grades ranging from clear to severe, and their results show that the accuracy of their method outperformed expert physicians.

Initially, we investigated the proportion of facial images in the most commonly used public datasets for skin disease, which include AtlasDerm , DermlS , the ISIC Archive , Derm101 and Dermnet. Most of these datasets did not provide information about body parts. In dermnet, which does provide body parts information, there were only 195 facial images. It is difficult to perform further research on facial skin diseases using such limited data. As a result, building a specialized dataset for face images is extremely necessary for our research.

III. EXISTING SYSTEM

Skin diseases recognition method based on image color and texture features diagnosing skin cancer using back propagation neural (BPN)network classifier. The Artificial Neural Networks constructed using a feed-forward architectural design detects skin diseases successfully based on patients symptoms and their habitat. A smart home system with in-built sensors and proposed artificial intelligence methods to diagnose the skin health condition of the residents of the house. Automatic skin lesions classification system using theory of transfer learning and pretrained deep neural network. A neural network is a mathematical model inspired by the transfer process of biological neuron information and its purpose is to learn a mapping from input to output. By using a loss function as a constraint and back propagation to optimize the parameters, this method can automatically learn complex tasks for different fields. This method has reduced the need for human labor, such as manual feature extraction and data reconstruction for classification. A CNN is a type of neural network. It generally consists of an input layer, many hidden convolutional layers and an output layer. Using this structure, the model can include a large number of parameters and obtain some usable properties such as equivariance, for image-related tasks.

However, for most diseases, the difference in symptoms on different body parts is not obvious. Therefore, when training the model for skin diseases, a better strategy would be to use the data of the whole body to train the model and then use it as a initialization and retrain model on images of a particular body part. Then, the model can be used to diagnose the diseases at that specific body part.

Unique features from the medical image are taken and are segmented using Histogram algorithm. The diseases are classified based on the histogram values and tolerance level value of the image. We taking into consideration of the mean values of images RGB (RED, GREEN, BLUE).The values ae calculated and the background of the images is considered to be black. This is not applicable for all images where the error in mean values may occur and the background of the image may not be black always. The proposed model does not take mean values and features are not extracted based on the histogram. So the possibility of the wrong classification of the image is avoided.

Image Gradient-The edge detector in most of image processing models uses an image gradient algorithm for edge detection. Using Image Gradient algorithm various points are not detected accurately. Differentiating the background pixels and foreground pixels will not be that much accurate. For example, differentiating the skin and the background will not be accurate. This is the major disadvantage of using image gradient algorithm. The proposed approach overcomes this issue. In the proposed system the features are extracted first various values differentiate the background and foreground pixels.

IV. PROPOSED SYSTEM

A.Inception V3: revolutionary model developed by google. It consists of two parts namely feature extraction and the other one is classification part. First, for the feature classification, the input image is sent to this model. In this model the input image size (299,299,3)The image must be of type jpg. The

images with larger size are made into this format. The features are classified on three major categories. They are high-level features, middle-level features, low-level features. In high-level feature, the entire image is considered.in middle-level features are extracted over the region. In low-level feature pixel by pixel features are extracted. When an input image is given the features are extracted first. The model is trained with approximately 15000 images with diseases class of around 90% of the trained data and 10% of the test data for our consideration. This model is used to predict diseases with n accuracy of around 94%.The output is provided in the form of a confusion matrix with actual and predicted diseases. Based on the confusion matrix we can predict the diseases types.

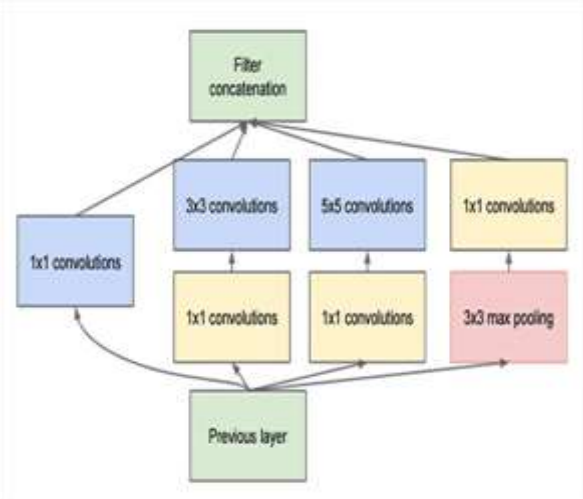

Fig.1. Architecture diagram of Inception V3

B.Xception is a deep convolutional neural network architecture that involves Depthwise separable convolutions. It was developed by Google researches. Google presented an interpretation of inception modules in convolutional neural networks as being an intermediate step in-between regular convolution and the depthwise separable convolution operation(a depthwise convolution followed by a pointwise convolution). In this light, a depthwise separable convolution can be understood as an inception module with a maximally large number of towers. This observation leads them to propose a novel deep convolutional neural network architecture inspired by Inception, where Inception modules have been replaced with depthwise separable convolutions. This model predict the diseases with an accuracy of 85.62%.

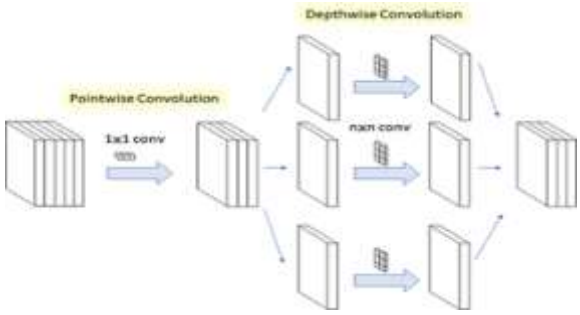

Fig.2. Architecture Diagram of Xception Module

C.VGG19:

It is a convolution neural network(CNN)architecture for image classification using deep learning. After the breakthrough provided by Alexnet in 2012 for the Imagenet Challenge competition, the next big breakthrough was by the VGG architecture with 16 convolutional layers and 3 fully connected layers. Totally 19 layers and hence the name VGG-19.

However VGG soon became mostly obsolete since it was trumped by smarter more computationally efficient architectures, namely Inception and Resnet. Also in the NAS approaches, a brave attempt was made to automatically learn the best architectures using Reinforcement learning. But it doesn't scale well to large data sets and large number of images classes. This kind of meta learning approach is hot these days. This model predicts the diseases with an accuracy of 83.36%.

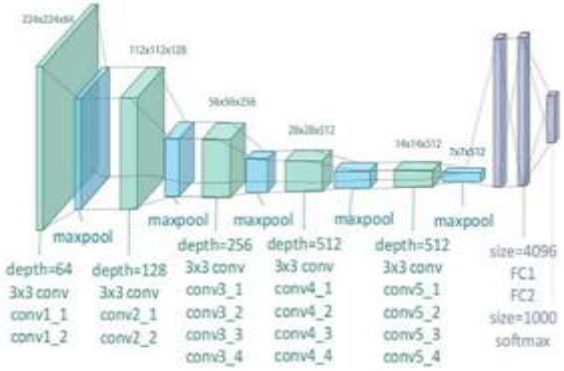

Fig.3. Architecture diagram of VGG19 Model

V. EVALUATIONS:

Dataset:

The images used in our work are collected from Kaggle Dermnet. It is an open source dataset contains various classes of affected skin images. Some of the classes of skin images are "Acne and Rosacea", "Atopic Dermatitis", "Bullous Disease", "Cellulitis

Impetigo", "Exanthems and Drug Eruptions", Hair Loss and Alopecia", "Herpes HPV", "Lupus and Connective Tissue Disorders", "Melanoma Skin Cancer", "Nail Fungus", "Poison Ivy Photos", "Psoriasis, Lichen Planus", "Scabies Lyme Diseases", "Seborrheic Keratoes", "Benign Tumors", "Systemic Disease", "Urticaria Hives", "Vascular Tumors" etc...

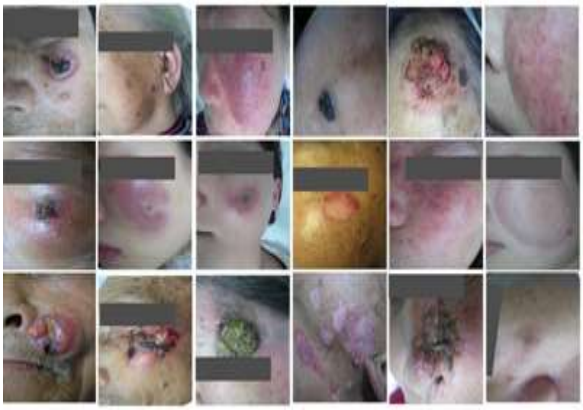

Fig.4. Images from Dermnet dataset

Evaluation metrics:

The metric used for analysing the three models is Confusion Matrix. It is calculated based on the images categorized for testing. Accuracy depends on the diagonal elements of the matrix. The diagonal elements represents that the actual images used for testing is predicted correctly. The x-line in the matrix indicates the number of predicted images for 20 classes of images. Similarly, the y-line denotes the number of actual images used for testing.

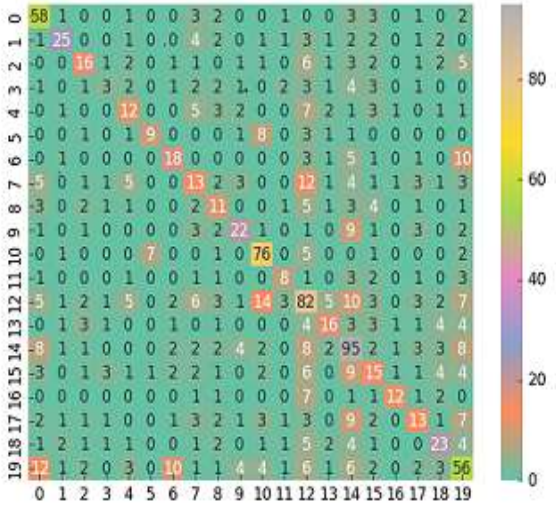

Fig.5. Confusion matrix of Inception V3

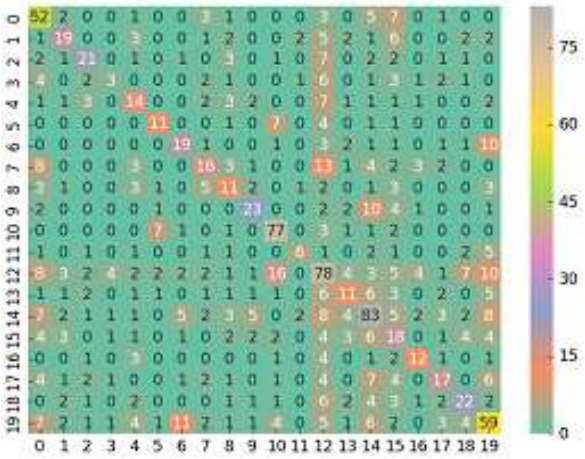

Fig.6. Confusion Matrix of Xception Model

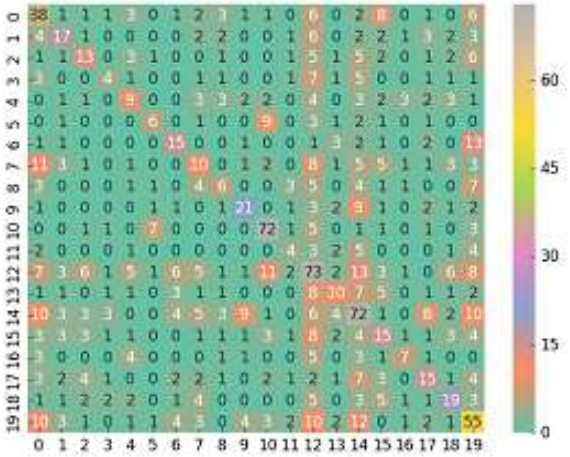

Fig.7. Confusion matrix of VGG19 Model

The following table represents the number of training and testing images on each dataset:

Classes of Diseases	Number of training images	Number of testing images
Acne and Rosacea	840	84
Atopic Dermatitis	489	50
Bullous Disease	448	45
Cellulitis Impetigo	288	29
Exanthems and Drug Eruptions	404	40
Hair loss and Alopecia	239	24
Herpes HPV	405	40
Light diseases and Pigmentation	568	57
Lupus and Connective Diseases	420	42
Melanoma Skin Cancer	463	46
Nail Fungus	1040	104
Poison Ivy Photos	259	26
Psoriasis, Lichen Planus	1405	141

Scabies Lyme	431	43
Seborrheic Keratoses and Benign Tumors	1371	137
Systemic Disease	606	61
Urticaria Hives	212	21
Vascular Tumors	482	48
Vasculitis Photos	416	42
Warts Molluscum	1086	109

VI.CONCLUSION

In this work, various skin diseases have been identified using three different architectures (Inception V3, Xception and VGG19). It is observed that Inception V3 has highest accuracy on training and testing these images on a whole. This is actually achievable due to logistic regression algorithm which uses probability as a tool to predict images.

ARCHITECTURE	RANK - 1	RANK - 5
INCEPTION V3	87.99%	94.28%
VGG19	65.49%	83.36%
XCEPTION	68.15%	85.62%

Inception V3 > Xception > VGG19

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