Identification of Skin Diseases using Parallel Convolutional Neural Networks

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Abstract - **Global Warming and Climate change has caused an increase in the number of people getting affected by Skin Diseases by a significant amount. However, diagnosing the Skin Diseases correctly is a challenging task. Deep Learning poses a solution to the problem of Identification of Skin Diseases. Considering the features of recently emerged Deep Learning Models in Convolutional Neural Network Architecture such as AlexNet, ResNet, MobileNetV1 which does a significant work by remembering the correct characteristics of the Image and Parallel Convolutional Neural Networks which gathers the diverse characteristics of the Image. The combined the use of both the architectures of Parallel Convolutional Neural Network with Deep Convolutional Neural Network branches to process the Image holds the key to analysis and accurate prediction. This ensemble approach has led to significant rise in performance of Deep Learning Model and correct Identification of unseen real-world data. Upon Training this model with Skin Disease Image Data we have developed a model to be used for skin disease detection.**

keywords - **Deep Learning, Parallel Convolutional Neural Network, Skin Diseases**

I. INTRODUCTION

As they say, "As technology develops, more diseases develop too". Diseases include skin diseases. The causes are the pollution done by humans on various resources. Due to these causes, the temperature of the earth has been rising every year. This phenomenon is called Global Warming. As the temperature increases, the integumentary system of humans gets affected easily by it. Integumentary system includes skins and the glands in it. Any unusual conditions in them are called skin diseases. Although there are various factors that cause skin diseases, global warming is one of them. If a person has a skin disease, after he/she discovers he/she has it, that person has to make a doctor's appointment in order to find what type of disease he/she has. After making the appointment, the person must wait till the time scheduled for him/her. Then, the person should report to the doctor at the time the appointment has been scheduled through any means of transportation. If the person could not reach the clinic in time, the whole appointment would be cancelled, and the person had to redo it again. Then, after the appointment, he/she must pay the consultation fee for the doctor just to find what disease it is. This traditional method consumes more time and money than the person thought. Since the technology grows along with the diseases, these diseases can be easily detected by it. Deep Learning is a subset of machine learning that is capable of learning from supervised or unsupervised from data that is structured, unstructured, labelled or unlabelled. Using deep learning, it is possible to detect the skin condition with the image of a skin. The neural networks play the most important role in deep learning which acts similar to the neurons of the brain. These neural networks can detect the difference in an image accurately. Hence, the neural networks can be used to detect the type of disease using the image of the skin.

II. LITERATURE REVIEW

Deep Convolutional Neural Networks has been revolutionary in image classification and their classification accuracy has been outstanding [8,6] when compared to traditional Machine Learning techniques. The Neural Network models with residual learning technique were highly capable of memorizing the input data [2,5] and provide accurate results with unseen real-world data. The development over the models with residual learning [7,9,10] technique enabled to capture the intricate details present in images rather than focusing on large scale features. Application of Deep Learning to detect the Skin abnormalities or diseases has led to a better way of diagnosis [3,4,11] the diseases. It is to be noted that the Parallel Convolutional Neural Networks has been capable of categorizing the image data efficiently [1,15,19] even with smaller datasets. The Application of very Deep Neural Networks to classify Skin Diseases has been a big break through because of their ability to correctly classify the real-world data [12,13,14] and significantly improving their performance. The Efficient Parallel Neural Networks with superficial residual layers have advocated the ability of Parallel Neural Networks to work with residual layers [17,18]. This has led to application of Parallel Convolutional Neural Networks to classify Image data consisting of intricate details [16]. The Parallel Training of Large-scale Training of Convolutional Neural Networks [20] has opened the possibility of adopting the residual learning technique into Parallel Convolutional Neural Network.

III. PRIOR WORK

Work on Skin Disease Detection

The performance of all existing DCNN models such as LeNet , AlexNet , ResNet , DenseNet on the Skin Disease data and their performance over those respective dataset helps to understand the impact of Deep Learning. They also discuss the Evaluation parameters and the necessity for higher pixel level accuracy for the performance of the model. The combined use of several weak classifiers leads to strong prediction results. The Authors have relied on the Transfer Learning Strategy and have performed Fine Tuning over the ResNet, DenseNet and MobileNet models. All those models already have memory of other objects. Though Transfer Learning has worked on given Dataset it has unreliability over unseen real-world Data.

Analysis of Deep Learning Models

Parallel Deep CNN overcomes the issues faced in the traditional method of Sequential Neural Network architecture in Parallel architecture. It states the usage of parallel branches of CNN's same architecture in order to process and remember the details of image in each of the respective branches the differential weight initialization allows each of the branches to understand the about the Image in a different way, thus covering the maximum features available in the Image. Concatenation of the layers allows the model to collectively analyse each information available in the Image and produce output. The limitation of this method is the absence of residual architecture without which the Neural Network cannot hold on the information in case of large amounts of Data.

IV. EXISTING SYSTEM

The major problems in traditional methods are more consumption of time and money. As the appointment has been booked, the person has to wait till the appointed by the doctor. This causes the disease to grow on that person. It may reach tertiary stage. Then, the person has to get a sick leave or postpone the work in order to meet the doctor. The person will be charged with an amount by the doctor when he consults the person. It affects both the most important things in life, Time, Money. The application of Machine Learning Models such as SVM, Linear Regression , Logistic Regression were unable to provide reliable results due to their inability to work on un seen real world images. The diagnosis process relied more on Medical Practitioner and test results, all of which involved more labor and time.

V. PROPOSED SYSTEM

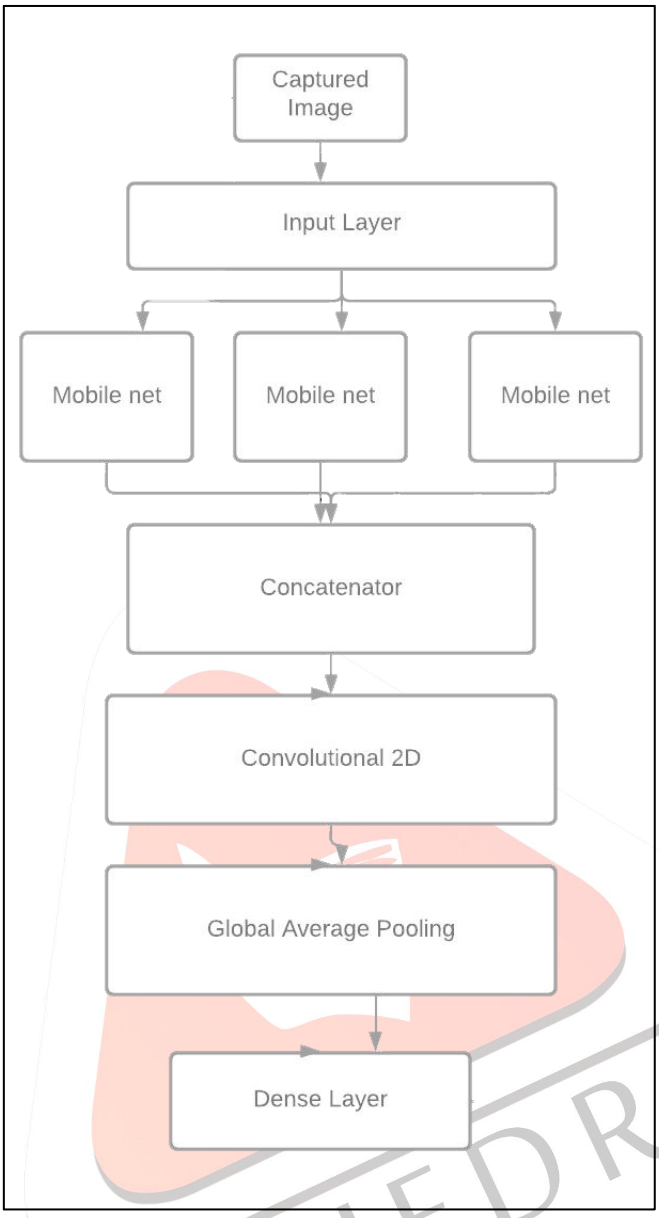
The proposed system consists of analysis of images using deep learning techniques. The person required to upload either capture a new picture or use an already taken picture in the website. The module analyses the images which classifies it and gives the disease name along with its symptoms, treatments in the very same page.

This System is capable of Identifying up to 6 different types of skin diseases such as Lyme Disease, Miliaria, Sunburn, Tinea Pedis, Actinic Keratoses, Bullous Impetigo, Dermatitis, Flea Bites. Apart from the above-mentioned disease cases the model can also identify the presence of disease-free skin and absence of skin in the image.

Standard Algorithm

Initialization weights to randomly generated value (small)
Set learning rate to a small value (positive)
Iteration n=1 ; Begin
for n< max iteration OR Cost function criteria met, do
for image x_1 to x_i , do
a. Forward propagate through convolution, pooling and fully connected layers
b. Derive Cost Fuction value for the image
c.Calculate error term δ(l) with respect to weights for each type of layers
Error gets propagated from layer to layer in the following sequence
i.fully connected layer
ii.pooling layer
iii.convolution layer
d.Calculate gradient ∇w(l)k and ∇b(l)k for weights ∇w(l)k and bias respectively for each layer
Gradient is calculated in the following sequence
i.convolution layer
ii.pooling layer
iii.fully connected layer
e.Update weights w(l)ji←w(l)ji+Δw(l)ji
f.Update bias b(l)j←b(l)j+Δb(l)j

Core Model Architecture Diagram



VI. System Design

The System has been developed in Python programming language using Tensorflow and Keras framework for Deep Learning and Flask Web Framework. The Website has been developed using HTML, CSS and Javascript. The System is divided into 3 different modules and function specification is listed as follows:

Image Capture Module

The Image Capture Module helps in capturing a picture of the user in a click. It has been implemented by javascript. Using navigator, the request for camera access will be asked. As soon as it gets the permission, the camera view has been captured. The captured view will be shown in the webpage through the navigator. When the capture button is clicked, a snapshot will be taken and converted into a 2D canvas which is downloaded automatically in the system. The Image capture module uses the Browser to access the Camera present in the System. The JavaScript runs a live video as a media stream as soon as the webpage is opened. The Capture button holds the function to freeze the frame and get the media as a Canvas. The Canvas is then converted into a Big Large Object and the BLOB is saved to Jpeg file format. The download function creates an element for file object. The Object's URL is accessed, the image file gets downloaded into the system.

Image Processing Module

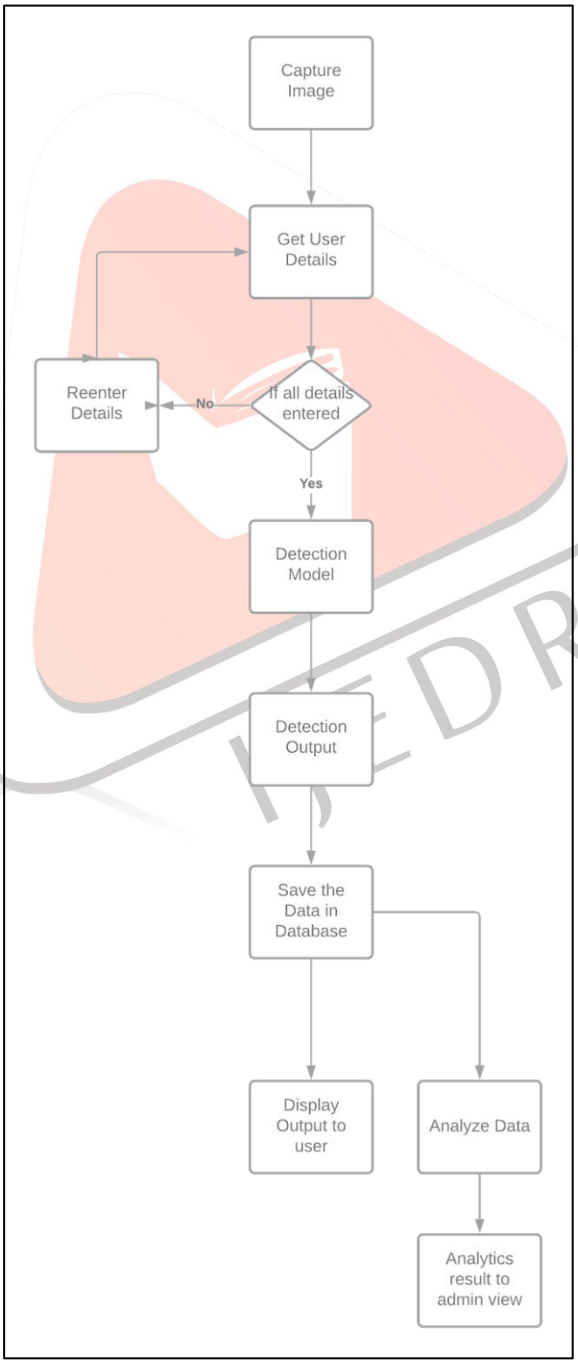
The image which was taken in the previous module or another picture (If the person already has a picture of the skin) must be uploaded along with their details in the submit page. Then, the image will be processed under the ANTIALIAS filter of the pillow library. The filtered image is converted into a numpy array which shows the image in an array format. To prevent the over usage of CPU, the values in the array had to be smaller as much as possible. It is achieved using normalization. The normalization process reduces the values in the range of 0-1. It helps in better processing in a very short span of time with accurate results.

Disease Detection and Analysis Module

The Keras library with Tensorflow as backend is used for analysis and detection. The inbuilt Keras functions contains Layers for Convolutional Neural Network and predefined deep learning models. The Normalised image is given as input to the neural network. The Parallel Convolutional Neural Network receives the Numpy array of image as input through the Input layer. The Input Layer is chained to three MobileNet Model (the weights of the models are initialized in random). The Output of the three models is merged in the Concatenation Layer. Then, the flow passes through Convolution and Dense Layers to the final output. The three MobileNet models with residual learning are trained by mapping and memorizing different aspects and details of the Image. The Concatenated output of the models provides a collective result with high accuracy. Output is processed and based upon the result; the web page gets redirected to the Result page. The Model can Identify whether Skin is present in the Input image and processes and provides output only if a clear image is present in the Image. If the Image uploaded does not contain any disease condition, then the Model returns the result as healthy skin. The Intuition that the PCNN model with 3 branches with each one to Identify absence of Skin, Identify Healthy Skin and to Detect the presence of Disease condition and provide exact result has worked successfully.

Data Flow

The process starts by capturing the image of the skin. Once the image of the skin is captured. The user will be asked to enter their details. These data will be later used for analytical purposes. The User will be prompted if they haven't filled the required fields. After entering the details, the image data will be sent to the server to detect the skin disease. Where the data will be processed and the detection result will be sent to the user. These data will be saved automatically in the database for future analytical purposes. The detection output will be displayed to the user along with suggestions of doctors nearby and medicines as well.



VII. Performance

The Parallel Deep Convolutional Neural Network model has 70.4% of f1 accuracy, macro average precision of 72.6% and weighted average precision of 73.0%. The model was trained on total of 2510 images.

VIII. Future Work

Introduction of detection of more diseases in the model is the next step. It makes the model to improvise prescreening of diseases with more reliability. The addition of new data sets along with the old one improves the accuracy of the model. The hyper parameter tuning and other performance results increase in accuracy makes the result better than the current result by improving accuracy. Deployment of the model in smartphones and edge devices makes it very easy to access by every individual. It reduces the processing time and latency.

IX. Conclusion

Followed by the demonstration of effectiveness Parallel Convolutional Neural Networks when applied to identify Skin Diseases. The Parallel Convolutional Neural Network has delivered promising results on deployment. This work encourages the use of Deep Learning methodologies in the field of Medical Science for the process of diagnosis and generation of accurate results with low latency. The next step in accordance with Skin Diseases is to increase the number of diseases Identifiable by the model to a significant level, baselining of the Parallel Convolutional Neural Network Model for Face and Object Detection Systems and Deployment of Quantized Parallel Convolutional Neural Network models into Mobile Devices.

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