A Novel Approach for Image Analysis to detect Skin Diseases through MobileNet

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Abstract -There are different skin conditions that prevail in the humid regions. Out of these conditions, there are certain life-threatening diseases which are quite common among the masses. The diseases like Basal Cell Carcinoma show up very much like Melanocytic Nevi (mole) on the skin and before they show up any other outwardly symptoms, the patient's health would have ghastly deteriorated. Most of these skin diseases can be cured if they can be detected at an early stage. A well known dataset, HAM10000 consisting of around 10015 images of different skin lesions was utilised after preprocessing it through two techniques. The techniques include Data Augmentation and Visual Attention. The reason behind conducting Data Augmentation is the lesser availability and unequal distribution of images into the seven chosen categories. The preprocessed images are fed into a lightweight CNN derived model known as MobileNetV2. This implementation has fetched an accuracy of 92%. The model was developed so that it can be accessed by anyone through a web browser. It is a web based application.

Key words : Classification of skin diseases, python, data augmentation, visual attention, Convolutional Neural Networks, MobileNetV2

I..INTRODUCTION

Skin diseases or lesions are the outwardly predominant signs/marks of a disease that affects the epithelial tissue of a human body. There is no particular reason for the cause of some of these diseases while some others are known to affect people living in certain areas with extreme climatic conditions. According to the Skin Cancer Foundation, Basal Cell Carcinoma(bcc) occurs due to prolonged exposure to Ultraviolet(UV) rays emanating from the Sun. It is one of the most common types of skin cancer. The paper [1] suggests the utilisation of MobileNet architecture along with LSTM. The idea is good but there is no efficient pre-processing technique involved. This might be the reason for the decrease in accuracy of the model. It is good to have a Visual Attention layer in the field of Computer Analysis of Clinical Images. This majorly contributes to the improvement of accuracy of the model. A simple classification of the skin lesion images based on texture, color scale without the utilisation of Artificial Neural Networks as in [2] shows the utilisation of Gray-Level Co Occurrence Matrix(GLCM). Though it has brought down the level of complexity to a greater extent, it has been observed by [3] that this method is sensitive towards image noise. A significant number of problematic images (images with extensively noticeable noise) has the capacity to affect the accuracy of the system. According to [4] there have been many lapses in the detection of deadly diseases by the physicians due to the lack of knowledge and data on the ever-evolving diseases. Instead of relying on the physical examination of the lesion and deciding upon the course of the treatment, it is sometimes good to take the opinion of an artificially trained neural network model. It doesn't downgrade the technical expertise of the physician or the dermatologist but provides additional support in the correct identification of the disease. Doctors often consider the help from trained neural network models for easier diagnosis and treatment like in [5],[6]. The proposed mechanism described here is capable of classifying the given input image into one of the seven different class : Vascular Skin Lesions (vasc), Benign Keratosis (bkl), Melanoma (mel), Actinic Keratoses (akiec), Basal Cell Carcinoma (bcc) and Dermatofibroma (df), Melanocytic Nevi (nv).

A melanocytic nevus (nv) (American spelling 'nevus'), or mole, is a typical considerate skin injury because of a nearby expansion of color cells (melanocytes). It is now and again called a nevocytic nevus or just 'naevus' (however note that there are different sorts of naevi). An earthy colored or dark melanocytic naevus contains the shade melanin, so may likewise be known as a pigmented nevus. Melanoma(mel) is a genuine type of skin malignant growth that starts in cells known as melanocytes. While it is less not unexpected than squamous cell carcinoma (scc) and basal cell carcinoma (bcc), melanoma is more hazardous in view of its capacity to spread to different organs all the more quickly in the event that it's anything but treated at a beginning phase.Basal cell carcinoma (bcc) is one of the most well-known types of skin malignant growth and the most regularly happening type, everything being equal. In the U.S. alone, an expected 3.6 million cases are analyzed every year. BCCs emerge from unusual, uncontrolled development of basal cells. seborrheic keratosis or Benign Keratosis (bkl) is a typical noncancerous skin development. Individuals will in general get a greater amount of them as they get more established. Seborrheic keratoses are normally earthy colored, dark or light tan. The developments look waxy, flaky and somewhat raised. They generally show up on the head, neck, chest or back. An actinic keratosis(akiec) is a harsh, layered fix on the skin that creates from long periods of sun openness. It's normally found on the face, lips, ears, lower arms, scalp, neck or back of the hands. Vascular sores (vasc) are generally basic irregularities of the skin and basic tissues, all the more regularly known as pigmentations. There are three significant classifications of vascular sores: Hemangiomas, Vascular Malformations, and Pyogenic Granulomas. While these skin pigmentations can seem to be comparable now and again, they each fluctuate as far as beginning and essential treatment Lastly, Dermatofibroma (Df) is a typical cutaneous knob of obscure etiology that happens all the more frequently in ladies. Dermatofibroma as often as possible creates on the limits (generally the lower legs) and is typically asymptomatic, despite the fact that pruritus and delicacy can be available. It is really the most well-known agonizing skin tumor.

II. METHODOLOGY

2.1 Architecture

A skin lesion image is first uploaded by the user from their web browser. The uploaded image is then cropped so that it's final dimensions after cropping are 224 x 224 x 3. This image is now fed into the MobileNet model for the prediction. The output is a list of probabilities for the image to be belonging to each class among seven different classes as mentioned in figure 1. Of these seven different probabilities, the top three are chosen and are displayed to the user.

CNN MobileNetV2 has been decided to be used here. The input size of the image given as input is 224x224x3 pixels. The parameters used to fit the model are : Adam's optimizer, categorical cross entropy, learning rate of 0.00001, softmax activation and number of epochs is 30.

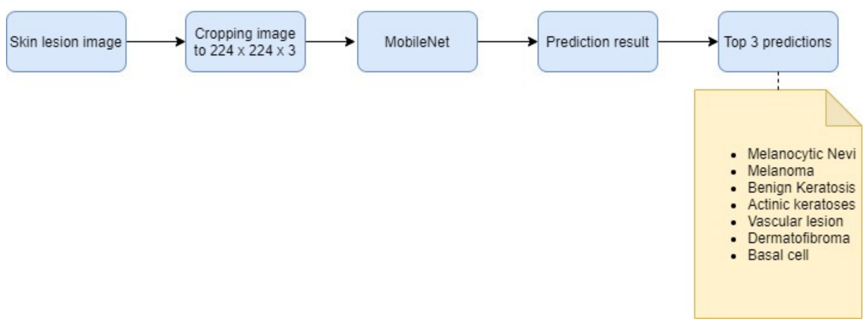

Figure 1 : Architecture Diagram

Mobilenet is based on depthwise distinct convolutions, with the exception of the principal layer. The principal layer is completely a convolutional layer. All of the layers are ended by Relu non-linearity and group standardization. The last but one layer feeds its input to a deciding softmax layer for providing the output. For the purpose of downsampling, convolution with strides is utilized for the convolutions just like in the first completely convolutional layer. The total layers in the MobileNet is 28 considering the both pointwise convolution and depthwise as discrete layers.

MobileNet uses deep solvable convolutions, each layer being followed by batch normalization and ReLU non-linearity. MobileNet contains a deep-convolution layer and a point-convolution layer. MobileNet uses input of shape 224 * 224 * 3. MobileNet's first layer is a convolutional layer with number of channels as 32, bits of 3 * 3 and with a step of 2. This is followed by ReLU non-linearity and BatchNormalization. After these first layers there is a sequence of cellular network blocks with different bit sizes and channels.

2.2 Dataset

Most of the data comes from an open data set called HAM10000. This data set was provided by [7]. The preparation of neural organizations for the mechanized determination of pigmented skin lesions is made difficult by the small size and the lack of a large number of accessible dermatoscopic data sets. We solve this problem with the HAM10000 data set ("Man vs. machine with 10,000 preparatory images"). We have compiled dermatoscopic images of different populations obtained with different modalities and stored. The latest dataset includes 10,015 dermatoscopic images that can fill cases with a variety of active ingredients of extremely significant indicative classes in the area of pigmented lesions: actinic keratosis and intraepithelial carcinoma / Bowen's disease (akiec), basal cell carcinoma (bcc), benign keratosis-like wounds (Sunlight-based lentigos / seborrheic keratosis and lichen planus such as keratosis, bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv) and vascular wounds (angiomas, angiokeratomas, granulomas and pyogenic secretions)(vasc).

There are two parts in the dataset where the first part has 5000 images and the second part has 5015 images along with a metadata file. Upon division of images into seven desired data folders, an unequal distribution of the images was observed.

Table 1 :Image Distribution Under Train Data

Category	Number of Images
Benign Keratosis (Bkl)	1020
Melanocytic Nevi (Nv)	5953
Actinic Keratoses (akiec)	302
Dermatofibroma (df)	108
Vascular Skin Lesions (vasc)	132
Melanoma (Mel)	1071
Basal Cell Carcinoma (bcc)	483

Table 2 : Image Distribution Under Test Data

Category	Number of Images
Benign Keratosis (Bkl)	76
Basal Cell Carcinoma (bcc)	31
Melanocytic Nevi (Nv)	752
Vascular Skin Lesions (vasc)	13
Dermatofibroma (df)	8
Melanoma (Mel)	38
Actinic Keratoses (akiec)	25

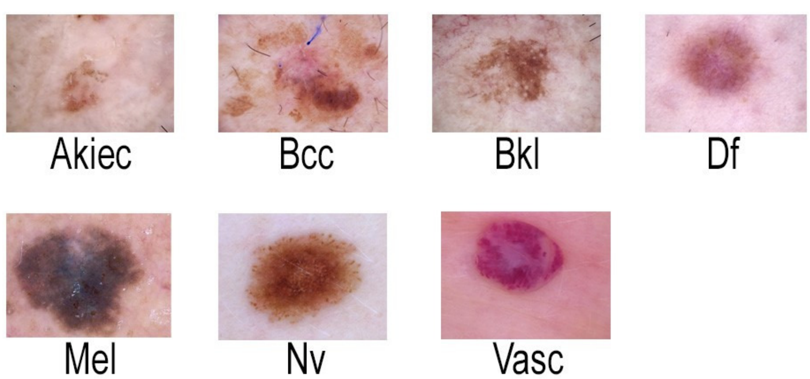

Figure 2 **:**Sample Images of Dataset

2.3 Data Pre Processing

Preprocessing of data is an important operation in any information mining paradigm. The expression "trash in, trash out" is especially related to information mining and Artificial Intelligence projects. Information gathering strategies are often grossly controlled, estimated outside the permissible range (e.g. amount : -10), mixed information that is incomprehensible (e.g. gender: male, pregnant: yes) and missing characteristics, etc. If not thoroughly pointed out these problems researched, it may give misleading results. In this way, the description and nature of the information precede any analysis. Information preprocessing is often the main phase of an AI project, especially in computational biology.

In the unfavourable circumstances that there is an existence of useless and too much data present or untrustworthy information, then that point of the preparation stage is quite troublesome. Information planning and dividing the steps can take a lot of time for preparation. Information preprocessing comprises cleaning, standardization, change, extraction and determination of valuable data, etc.

2.3.1 Data Augmentation

Information expansion in information investigation are methods used to expand the measure of information by adding marginally changed duplicates of previously existing information or recently made engineered information from existing information. It's anything but a regularizer and diminishes overfitting when preparing an AI model.[1] It is firmly identified with oversampling in information investigation.

In the event that the issue of information shortage is confronted, the basic yet compelling procedures, for example, changes may represent a restricted arrangement. In the event that a dataset is too little, a changed picture set through turn and reflection and so on may in any case be excessively little for a given issue. Another arrangement is the sourcing of altogether new and engineered pictures through different methods, for instance the utilization of Generative ill-disposed organizations to make new manufactured pictures for information augmentation.[1] Additionally, picture acknowledgment calculations show improvement while moving from manufactured pictures created by the Unity Game Engine,[3] that is, to improve learning of true information by enlarging the preparation interaction with delivered pictures from virtual conditions. The process of data incrementation can be viewed as increasing the number of images by replicating the existing images through rotation, zooming, cropping etc. Preparing deep learning neural organization models with more information can produce more powerful models, and augmentation strategies can produce variants of the images that can improve the ability of adaptation models to summarize what they discovered when creating new images. Tensorflow provides a solution for data augmentation in the form of a method in keras. The method's name is ImageDataGenerator. By providing certain parameters that describe the degree of rotation, zoom, crop and number of images to be generated, this method does all the work automatically.

Table 3 :Image Distribution Under Train Data after Data Augmentation

Category	Number of Images
Basal Cell Carcinoma (bcc)	5859
Dermatofibroma (df)	4410
Vascular Skin Lesions (vasc)	5290
Melanocytic Nevi (Nv)	5954
Actinic Keratoses (akiec)	5217
Benign Keratosis (Bkl)	5920
Melanoma (Mel)	5930

As observed, there are an unequal number of images in each folder category. This causes several skewed class distributions thus resulting in unequal miscalculation of costs. Data augmentation was the method used for overcoming this problem. The class with a lesser number of images is considered and the images are replicated by making some modifications like rotations, cropping and slight changes to pixels.

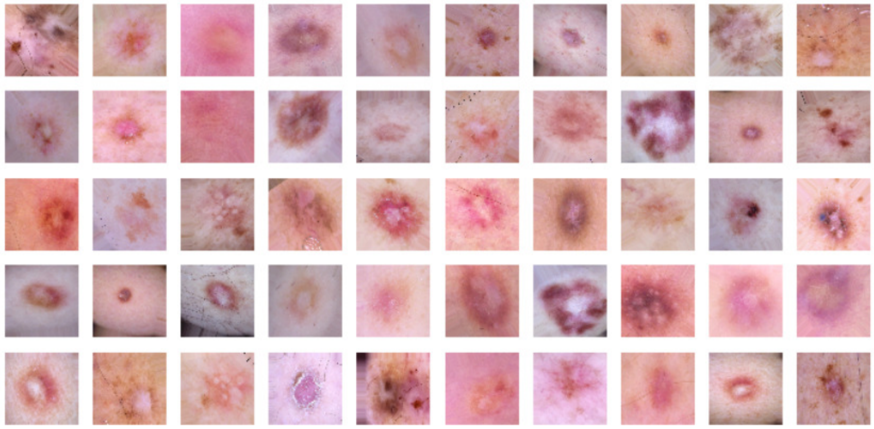

Figure 3 : Sample Augmented Images

Another technique of Visual Attention has also been employed to further boost the accuracy. According to research [8], CNNs tend to have a redundant use of information while feature extraction.

2.4 Inference Algorithm

After the training is done, the weights can be saved with the help of save() method. A model.h5 keras file is created which can be used for further predicting the output for new data. The size of this file is 26.89 MB. This file is converted into a web browser understandable format with the help of aTensorflow library known as 'Tensorflowjs'. This library converts the model.h5 into a json and javascript file. The reason behind utilisation of Tensorflowjs library is to safeguard the privacy of the data of the patient. Usage of Flask for User Interface implementation requires for the user image to be transferred over to the server side. Any data breach at the server side might put the data of all patients at a risk. So, instead of transfer of image to server side the model is loaded directly onto the user's machine. This is made possible with the vital combination of MobileNet and Tensorflowjs.

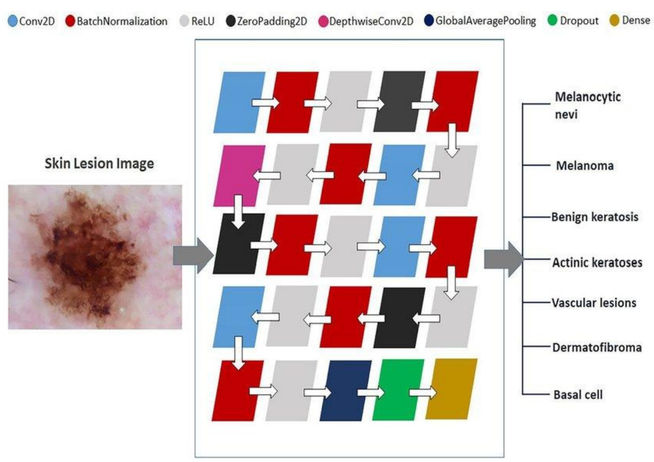

Figure 4 : Detailed Overview

2.5 User Interface - Web Application

The web application that was developed using the generated json and javascript files has three main steps. First step involves loading of the model when the user launches the application. It hardly takes 30 seconds for the model to load. In the second step, the user is prompted to upload an image for the purpose of detection of the anomaly. The third step involves displaying the results. The top three most probable classes are displayed to the user along with their probabilities. The display of three probable classes will give more flexibility to the physician or dermatologist and also leaves room for error on part of the system.

Figure 5 : Graphical User Interface of Web Application

III. RESULTS

The accuracy obtained with the trained model is around 96%. The below data shows the accuracy of the model while training and validation across epochs.

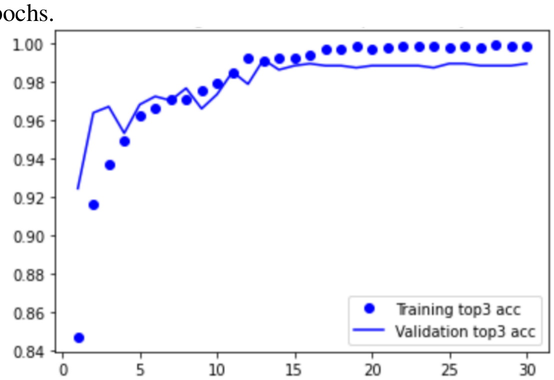

Figure 6 : Graph Representing Training and Validation Accuracy

The below figure emphasizes the confusion matrix of the model applied on the test data.

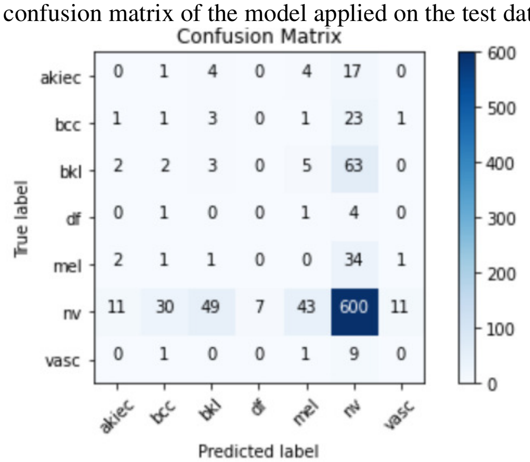

Figure 7 : Confusion Matrix on Test Data

From the above results it can be inferred that data augmentation and visual attention mechanisms have helped a lot in achieving this accuracy.

IV. CONCLUSION

The project has acquired an accuracy of more than 96% while detecting seven different classes of skin conditions. Upon cross checking with other available models, it is safe to consider that augmentation of data and application of another layer of visual attention has helped this project a lot to gain the upperhand in terms of accuracy. By processing the input image on the user-end, the user is safeguarded from a possible data breach. Medical data is given utmost priority when it comes to data security. It is believed that many lives could be saved by identifying a skin lesion correctly and at an early stage. Identifying a disease correctly is as important as identification of it at an early stage. Upon observation, both of the above conditions have been met successfully. Under future works, a more advanced attention layer like self-attention or deep-attention can be put into use. If more data is provided or is made available by any source, it would be a great boost to the model's dependability as there wouldn't be need to augment the data. Real world images are far better than generated images.

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