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Empirical algorithm to detect skin disease using deep convolution neural networks through mobilenet algorithm

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Abstract

Skin conditions are common and have grew in recent years, according to the abstract. Skin conditions must be promptly and accurately diagnosed in order to improve patient outcomes and provide appropriate care. The subjective and time-consuming manual diagnosis procedures dermatologists use necessitate the use of automated techniques to improve accuracy and efficiency. This work aims to make use of the 1,000-item. We applied Deep Convolution Neural Networks that have been successful with the ImageNet dataset at classifying seven different types of skin lesions.With the MobileNet Model we produced results that are 95% accurate. By this model we are able to achieve more accuracy than previous one.

This model makes use of Keras and TensorFlow, both of which are implemented in Python 3.8.0. This model precisely finds seven sorts of skin diseases with an exactness of 95%. The results of the experiments confirm the intuition that pre-trained models advance highlights, and the geographic properties of DCNNs aid in learning highlights for a dataset of skin lesions dermatoscopic images, which originates from something altogether different.

Subject Classification: *18C10.*

Keywords: *Deep learning, Keras, Tensor flow, KNN, Mobilenet model.*

1. Introduction

The prevalence of skin conditions varies across the world based on the problem at hand and the area in question. Yet, skin conditions are common all over the world and can significantly lower people's quality of life. [1] Skin conditions impact over worldwide 900 million people, making it one of the most prevalent non-communicable illnesses, according to the World Health Organization. Acne, eczema, psoriasis, rosacea, vitiligo, skin cancer, and infectious disorders including impetigo and fungal infections are examples of common skin problems.

Skin diseases are especially prevalent in low- and middle-income countries where access to medical care and treatments may be restricted [2]. For instance, leprosy and Buruli ulcer are neglected tropical illnesses

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that can severely destroy skin and leave patients disabled [3]. In addition, skin diseases can also have social and psychological consequences, such as stigma, anxiety and depression [4]. Therefore the prevention and management of skin diseases are essential for improving individuals' health and well-being globally. The classification of pictures is a broad category that can encompass any issues requiring the ability to distinguish between images of various objects [5][6].Deep CNN has the distinctive feature that its very last levels of the network acquire semantics and high-level properties. The initial layers, in contrast, typically learn very general and "low-level" characteristics of images [6][7]. After being trained for one image classification task on one dataset, Deep Convolutional Neural Networks can be used for many image classification tasks utilizing different datasets [8]-13].Deep learning employs multiple processing layers to represent data in a hierarchical manner. It provide a techniques for using a tiny amount team of feature engineers to manage large data [14].

2. Literature Review

In order to produce work that is more accurate, we intend to scan and review a number of source documents prior to beginning this procedure.

An introduction to the paper that we intend to scan prior to beginning this work is provided here. Examining these publications reveals that a variety of legitimate approaches to disorder prediction, classification, and measurement have been proposed by researchers. For the precise identification, classification, and measurement of skin diseases, researchers have developed numerous novel strategies. This section includes their autumnal work.

Skin Disease was detected using Image Augmentation Strategy for segmentation and CNN is used as a classifier. The total dataset of 2500 images was used.This attained the accuracy of 84.15% [2].

The authors showed the Face Disease Detection with the precision of 84.79%.The dataset consist of 775images.K-means clustering is used for Segmentation and SVM is used for classifier [3].

The research [4] showed the Skin Disease Detection along with the precision of 73%.The dataset consist of 2500 images. Ostu's Method is used for Segmentation and kernel SVM is used for classifier.

The research showed the Eczema, Melanoma, Psoriasis Disease Detection with the precision of 79%.The dataset consist of 100 images.

Ostu's Method is used for Segmentation and kernel SVM is used for classifier [5].

The paper for the Skin lesion Diagnosid with the precision of 83% [7] [11].The dataset is taken from dermnet.com .Convolution Neural Network is used for Segmentation and SoftMax Image Classifier is used for classifier [8][13].

The Malignment Disease Detection with the precision of 80.90%.The dataset consist of 775 images.K-means clustering is used for Segmentation and CNN is used for classifier [18].

Related Work

The development of a system for detecting skin conditions is our objective. As the starting point for image processing, the end user should upload the picture of the illness skin. Using the Mobilenet Model, the skin disease can be predicted. The suggested system's objectives are as follows:

1. Create a user-friendly web application specifically for farmers.
2. Determine precise outcomes depending on the input image.
3. Project corrective and preventive actions for the detected ailment.

Disease specific to skin include:

- Melanocytic nevi
- Melanoma
- Actinic keratoses
- Benign Keratoses
- Vascular Skin lesion

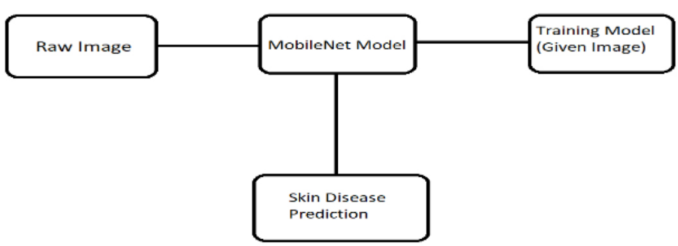

Figure 1

Manual process of model

- Basal cell carcinoma
- Dermatofibronoma

Figure 1 and 2 shows the process and algorithm flow. The input test image is captured and pre-processed in the next step. The selected database has been properly split and computed. The model has been successfully trained by Mobilenet Model.

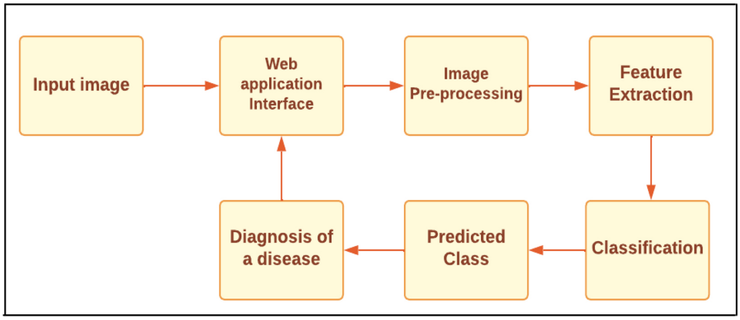

Figure 2

Algorithm Flow

4. Methodology

A. *MobileNet-Model*

MobileNet, a CNN architecture, enables the effective integration of Computer Vision into tiny amount, movable objects, such as phones and robots, instead of noticeably sacrificing accuracy. A basic MobileNet has 4.2 million total parameters, that is fewer than little bit of the other CNN systems[12].

Additionally, MobileNets adds two new global hyperparameters that are modifiable, allowing model developers to decide the exact size of their models depends on (and sacrifices accuracy). In contrast, the values of the numerous input picture channels are combined and filtered by a traditional convolution method in a single phase[17][19].

The standard convolutional layer of the depthwise separable layer described above would have N selected of dimension $\mathbf{D_K \times D_K \times M}$. because the input image's dimension is $\mathbf{D_F \times D_F \times M}$.That may be a also outcome in an output image at dimension $\mathbf{(D_F\text{-}D_K+1) \times (D_F\text{-}D_K+1) \times N}$.

The total cost of computation will be $D_K \times D_K \times M \times N \times (D_F\text{-}\mathbf{D_K+1}) \times \mathbf{(D_F\text{-}D_K+1)}$.

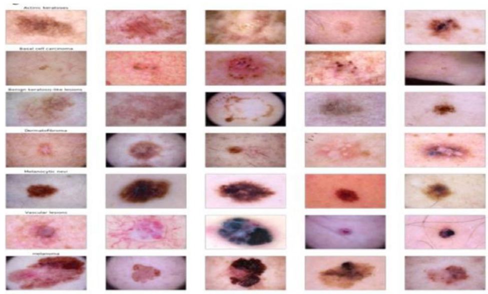

Figure 3

Input Data Sample

To similar the two costs evaluated, lets classify one with the other:

$(\mathbf{D_K} \times \mathbf{D_K} \times M \times (\mathbf{D_F} \times \mathbf{D_K}-1)) \times (\mathbf{D_F} - \mathbf{D_K}+1) + (M \times N \times (\mathbf{D_F} - \mathbf{D_K} + 1)) \times (\mathbf{D_F} - \mathbf{D_K} + 1)\ \mathbf{D_K} \times \mathbf{D_K} \times M \times N \times (\mathbf{D_F} - \mathbf{D_K} + 1) \times (\mathbf{D_F} - \mathbf{D_K} + 1)$

Sample 1:

Figure 3 shows the input data. Figure 4, 5, 6, 7 and 8 shows the execution steps.

Figure 4

Execution screenshot

Sample 2:

Figure 5

Execution screenshot

Sample 3:

Figure 6

Execution screenshot

Sample 4:

Figure 7

Execution screenshot

Sample 5:

Figure 8

Execution screenshot

5. Result

Experimental setup

For training the model, we have taken images from the Harvard Dataverse Platform. Wehave used a dataset of 1000 images to find out the working of the Mobilenet model. Further validation and normalization of the data are done to train the dataset. Trained data is used for further processing. To normalize the dataset scaling function is used. The application of a global average pooling layer that average pools the spatial dimensions until they are all equal to one while maintaining the integrity of the other dimensions. Table 1 shows the result.

Table 1

Result

Models	Validation	Test	Depth
Baseline	77.48%	76.48%	11 layers
Fine-tuned VGG16	79.82%	79.64%	23 layers
Fine-tuned Inception V3	79.935%	79.94%	315 layers
Fine-tuned Inception-ResNet V2	80.82%	82.53%	784 layers
Fine-tuned DenseNet 201	85.8%	83.9%	711 layers
Fine-tuned Inception V3	86.92%	86.826%	-
MobileNet	95%	94.8%	-

Performance Analysis

We have trained the model with 30 epochs where The total number of images processed once each forward and backward individually in a convolution neural network constitutes one epoch (CNN). System performance analysis is done in Figure 9 and 10.

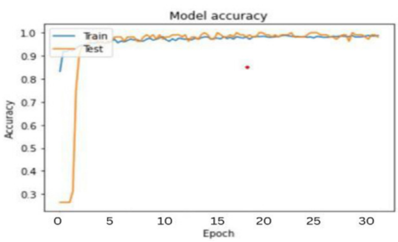

Figure 9

Accuracy

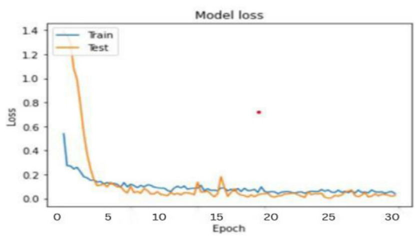

Figure 10

Model Loss

One epoch = (number of iterations x batch size)/ (Total no of images in the training).

Train model with 30 epochs.The models validation accuracy is 0.9481 and its training accuracy is 0.95. 95% of the model's accuracy was attained using 30 sample epochs.

6. Conclusion

An application for diagnosing skin conditions and offering treatment recommendations has been developed. As a result, the proposed goal was implemented for skin diseases. The result shows the suggested strategy has the ability to distinguish between the disorder with little computational effort. With the utilization of this framework, skin illness might be distinguished right off the bat, and by applying appropriate treatment, issues can be settled with the least sum. This will help to detect the skin problem early in rural populations. Mobilenet model is presented in the proposed study to address the issue of disease identification in various skin diseases.

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