A Novel Light Weight Approach For Identification of Psoriasis Affected Skin Lesion Using Deep Learning.

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Abstract. Psoriasis is a skin disorder which affects the people physically, mentally and emotionally. It is characterized as rough elevated scaly skin which is evident from surrounding skin area. There are various types of psoriasis which include plaque psoriasis, nail psoriasis, guttate psoriasis, inverse psoriasis, pustular psoriasis, erythrodermic psoriasis and psoriatic arthritis. The common trend observed is that the people tend to face difficulties in differentiating and tracking the disorder which will worsen the situation of the affected skin. It is essential to keep track of the affected skin for the prognosis of the disorder. In this work, an attempt is made to identify the psoriasis affected area automatically using MobileNet machine learning model which will become an objective tool in accurate identification of the disorder which in turn helps in effective treatment of the disorder.

1. Introduction
Psoriasis is typical skin disease which can last for many years. It is characterized by an elevation with decolored skin from its surroundings in the human body. The elevated skin lesion may be rashed, aberrated or sometimes scaly and patchy. The psoriasis disorder is initiated primarily by the abnormalities in the immune system and secondary factors such as lifestyle habits, stress. It is very much easier to treat the long-established untreated psoriasis rather than to treat the already treated psoriasis as the therapy makes the affected skin more complicated which in turn makes it difficult clinically and histopathologically.

It is also the case where early treatment of psoriasis can create confusions, which sometime gets cleared as the time ellipses as the most of the cases exhibit clear characteristics of psoriasis with the aid of skin biopsy and continuous observation of affected skin. It is essential to do accurate diagnosis of psoriasis as most of the treatments are inappropriate for treating psoriasis as in the case of inflammatory dermatomes which is actually treated by steroids, which are much proven line of treatment for inflammatory dermatomes but can be hazardous when the same steroids are used for treating psoriasis. It is largely observed that in the early stage of psoriasis which is also called as plaque stage, plaques are raised compared to normal skin containing silvery scales. In some cases, plaques are not clearly visible, such cases can be identified by gently tapping the skin or scratching the affected part. There are many types of psoriasis based on the texture and the place of occurrence. The various types of psoriasis include plaque psoriasis, nail psoriasis, guttate psoriasis, inverse psoriasis, pustular psoriasis, erythrodermic psoriasis and psoriatic arthritis. On an average 80% to 90% of the cases are of plaque psoriasis which is characterized by dry red scaly lesions which predominantly occur on knees and elbows. The literature survey also reveals that there exist a strong relationship between stress and psoriasis. In the latest literature, the researchers describe psoriasis...
disorder as neurogenic mediated disease which is described as inflammation caused due to physiological stress process where mediators are released in blood stream by cutaneous nerve which will result in inflammatory reaction by skin which will generate local inflammation and cause psoriasis. The work is an attempt to automatically classify psoriasis affected skin area from normal healthy skin using machine learning algorithm. We have used MobileNet machine learning model as it is light weight and turnaround time is also less compared with other machine learning models. It basically consists of light weight deep convolution neural networks that are much smaller and faster than many of the popular models of machine learning models. MobileNets are a class of small low powered neural networks that can be used for classification and detection. Since they are small, they can be considered to implement on handheld mobile devices hence they are as MobileNet.

| Model       | Size  | Number of Parameters |
|-------------|-------|----------------------|
| MobileNet   | 16 MB | 4,253,864             |
| NASNetLarge | 343 MB| 88,949,818            |

The above table provides the comparison of the size and the number of parameters of MobileNet and NASNetLarge. It is observed that MobileNet occupies 16 MB space on the disk whereas NASNetLarge occupies 343 MB of space on the disk which is nearly around 20 times larger than MobileNet. The size difference is basically due to the number of parameters, number of weights and biases contained in the model. Compared to heavy models such as NASNetLarge, MobileNet lacks accuracy which is a trade-off of light weight model. MobileNet is originally trained on ImageNet library. So we will be using the pre trained weights in the experiments at initial stages.

2. Methodology

Identification of psoriasis affected skin area boils down to classification of the skin into healthy skin and affected skin. In this work we use MobileNet machine learning model to identify the healthy skin from affected skin. The experiment consists of identification of psoriasis affected skin lesions from normal healthy skin.

The automatic identification of psoriasis affected skin lesions is a complex task due to the fact that other abnormalities of the skin may also add to the inter class variations. The psoriasis affected skin datasets are built using samples collected from mainly two sources which include Department of Skin...
and STD, Karnataka Institute of Medical Sciences, Hubli, Karnataka, India and Department of Dermatology, Navodaya Medical College, Raichur, Karnataka. The normal skin images are collected from students of Department of Computer Science, Rani Channamma University, Belagavi. An attempt was also made to collect images from internet, but the images are not used for the experiment as they were found to have noise and were enhanced using various image processing tools. The experiments were carried out using Jupyter Notebook as IDE which is run with Anaconda distribution of Python 3.7.6. The hardware used is Intel Core i5, 8th Generation configured with 16GB RAM, Keras machine learning neural network library and TensorFlow frameworks are used in the experiment. The experiments are carried out using core layers of MobileNet model. Pre configured weights from ImageNet are used with no trainable parameters as one of the case. Subsequent experiments were carried out by enabling the parameters to train during training phase. The collected psoriasis images cannot be directly used for the processing. The collected images are preprocessed by resizing the images to 224 X 224. This is done by keras function ImageDataGenerator() along with target_size=(224,224) as a parameter.

MobileNet Model – The MobileNet architecture is shown below in figure 3 and figure 4. The model consists of Convolution layer, Zero Padding layer, Batch Normalization layer, ReLU layer and blocks of Depthwise Convolutions. Again Depthwise Convolution block contains Depthwise Convolution, Batch Normalization, ReLU, Convolution, Batch Normalization and ReLU layers. In convolution layer a tensor is created from the sample input images with the size of 224 X 224 X 3 which are image height, image width, and the number of layer. The created tensor is convoluted with the kernel to get the output of the convolution layer which forms input to the next layer. In batch normalization layer, normalization and standardization have a typical goal of transforming the input feature data to a same common scale. It will normalize the numerical data to a data scale from 0 to 1. The process involves subtracting the mean of the data set from each sample and dividing the resultant by standard deviation.

\[
Z = \frac{X - \text{Mean}}{\text{Standard Deviation}}
\]

It is always seen that many features of input data may be represented on to a different scale, so when normalization is applied to such data, all the data is brought to a scale of 0 to 1 and the processing becomes easy, which in turn will avoid data instability. Another observation made in machine learning is that if the large input data is fed to the network, then training speed is drastically hampered. In batch normalization, output of the activation function is normalized as shown in equation 1, and in second stage the resultant is added with an arbitrary constant “a” as shown in the equation 2. In the third step the resultant is multiplied with an arbitrary constant “b” as shown in equation 3.

\[
Z_1 = Z + a
\]

\[
Z_2 = Z_1 \times b
\]
In the first instance, the experiment contains a training set of 20408 images which are divided into two classes namely psoriasis unaffected and psoriasis affected, where as validation set contains 9896 images which are again divided into two classes namely psoriasis unaffected and psoriasis affected and testing set contains 3600 images which are again divided into two classes namely psoriasis unaffected and psoriasis affected. Each input image is sub divided into 224 X 224 which is the required input size for MobileNet architecture. The batch size is the hyper parameter which signifies the number of samples that will be passed through the network at one time. After many iterations, the batch size is chosen to 20, as the larger batch may provide over fitting results. The pre trained weights of ImageNet are used for the experiment. The activation function used is softmax. The results of the experiment are as below.
Figure 5. Training loss, validation loss, training accuracy, validation accuracy of the data with the pretrained weights from ImageNet.

The details of the parameters used in the experiment area as below. As we have used the pretrained weights of imagenet, the value of trainable parameter is zero.

Table 2. Comparison of total parameters, trainable parameters, non-trainable parameters with the weights from ImageNet.

|                         | Total parameters | Trainable parameters | Non-trainable parameters |
|-------------------------|------------------|----------------------|--------------------------|
|                         | 4,255,866        | 0                    | 4,255,866                |

The analysis of the trainable parameters is explained as below.
The first layer which is input layer and the next layer which is zero padding layers do not contribute any counts to the parameters as these being initial inputs.

The next layer is convolution layer, is with 3 inputs, 32 filters and the size of filter being 3X3, so

Parameters = Number of inputs * Number of filters * Size of filters
= 3*32*(3 X 3)
= 864.

The next layer is Batch Normalization layer with 32 inputs, and for Batch Normalization layer numbers of parameters are calculated as:
Parameters = Number of inputs * 4
= 32*4
= 128.

In the next layers we have continuous blocks of Depthwise Convolutions, which contains Depthwise Convolutions, Batch Normalization, ReLU, Convolution, Batch Normalization, and ReLU layers sequentially.

In the first Depthwise Convolutions block, the first layer is Depthwise Convolution so, the parameters are calculated as below:
Parameters = Number of inputs * Size of filters
= 32*(3 X 3)
= 32*9
= 288.

The second layer in Depthwise Convolutions block is Batch Normalization which has 32 filters, so the parameters are calculated as below:
Parameters = Number of filters * 4
= 32*4
= 128.
The third layer in Depthwise Convolutions block is ReLU, which does not have any parameters. The fourth layer is normal convolution layer with 64 filters, with 32 inputs, and the size of filter being 3 X 3, so the number of parameters is calculated as below:

\[ \text{Parameters} = \text{Number of Inputs} \times \text{Number of filters} \]
\[ = 32 \times 64 \]
\[ = 2048. \]

The next layer is Batch Normalization which has 32 filters, so the parameters are calculated as below:

\[ \text{Parameters} = \text{Number of filters} \times 4 \]
\[ = 64 \times 4 \]
\[ = 256. \]

The last layer in the block is Depthwise Convolutions block is ReLU, which does not have any parameters. So all the blocks repeats itself for 13 times. The sum total of these 13 blocks is calculated based on Number of Inputs, Size of filters and Number of filters fed at each level. So after adding all the above parameters, the total number of parameters will be 4,255,866 which are not trainable.

The Confusion matrix of the experiment is plotted as below. Out of total images which were fed for the classification, 50% of the affected images were classified as affected while other were classified as unaffected.

![Confusion Matrix](image)

**Figure 6.** Confusion matrix for the classification with the pretrained weights from ImageNet representing performance of a classification.

The second experiment is aimed to introduce the trainable parameters in the network. Here we are making the parameters of last five layers of the network as trainable. In this experiment the network starts to learn from the actual samples. The summary of the results is tabulated as below.

**Table 3.** Comparison of total parameters, trainable parameters, non-trainable parameters with five trainable layers.

| Total parameters | Trainable parameters | Non-trainable parameters |
|------------------|----------------------|-------------------------|
| 4,255,866        | 1,027,002            | 3,228,864               |
The results of the experiment are as below:

![Training Loss and Accuracy on Dataset](image1.png)

**Figure 7.** Training loss, validation loss, training accuracy, validation accuracy of the data with five trainable layers.

![Confusion Matrix](image2.png)

**Figure 8.** Confusion matrix for the classification for the data with five trainable layers representing performance of the classification.

The third experiment is aimed to introduce the still more trainable parameters in the network. Here we are making the parameters of last ten layers of the network as trainable. In this experiment the network starts to learn from the last ten layers. The summary of the results is tabulated as below.

**Table 4.** Comparison of total parameters, trainable parameters, non-trainable parameters with ten trainable layers.

|                         | Total parameters | Trainable parameters | Non-trainable parameters |
|-------------------------|------------------|----------------------|--------------------------|
|                         | 4,255,866        | 2,077,626            | 2,178,240                |

![Training Loss and Accuracy on Dataset](image3.png)

**Figure 9.** Training loss, validation loss, training accuracy, validation accuracy of the data with ten trainable layers.

![Confusion Matrix](image4.png)

**Figure 10.** Confusion matrix for the classification for the data with ten trainable layers representing performance of the classification.
The fourth experiment is aimed to introduce the still more trainable parameters in the network. Here we are making the parameters of last fifteen layers of the network as trainable. In this experiment the network starts to learn from the last fifteen layers. The summary of the results is tabulated as below.

**Table 5.** Comparison of total parameters, trainable layers, trainable parameters, non-trainable parameters with fifteen

| Total parameters | Trainable parameters | Non-trainable parameters |
|------------------|----------------------|--------------------------|
| 4,255,866        | 2,615,226            | 1,640,640                |

![Figure 11](image1.png) **Figure 11.** Training loss, validation loss, training accuracy, validation accuracy of the data with fifteen layers trainable layers.

![Figure 12](image2.png) **Figure 12.** Confusion matrix for the classification for the data with fifteen layers trainable layers representing performance of the classification.

The fifth experiment is aimed to introduce the still more trainable parameters in the network. Here we are making the parameters of last twenty layers of the network as trainable. In this experiment the network starts to learn from the last twenty layers. The summary of the results is tabulated as below.

**Table 6.** Comparison of total parameters, trainable parameters, non-trainable parameters with twenty trainable layers.

| Total parameters | Trainable parameters | Non-trainable parameters |
|------------------|----------------------|--------------------------|
| 4,255,866        | 2,620,858            | 1,635,008                |

![Figure 13](image3.png) **Figure 13.** Training loss, validation loss, training accuracy, validation accuracy of the data with twenty layers trainable layers.

![Figure 14](image4.png) **Figure 14.** Confusion matrix of classification for the data with twenty trainable layers representing performance of the classification.
The sixth experiment is aimed to introduce the still more trainable parameters in the network. Here we are making the parameters of last twenty five layers of the network as trainable. In this experiment the network starts to learn from the last twenty five layers. The summary of the results is tabulated as below.

### Table 7. Comparison of total parameters, trainable parameters, non-trainable parameters with twenty five trainable layers.

| Total parameters | Trainable parameters | Non-trainable parameters |
|------------------|----------------------|--------------------------|
| 4,255,866        | 2,889,658            | 1,366,208                |

![Figure 15. Training loss, validation loss, training accuracy, validation accuracy of the data with twenty five layers trainable layers.](image1)

![Figure 16. Confusion matrix for the classification for the data with twenty five trainable layers representing performance of the classification.](image2)

The seventh experiment is aimed to introduce the still more trainable parameters in the network. Here we are making the parameters of last thirty layers of the network as trainable. In this experiment the network starts to learn from the last thirty layers. The summary of the results is tabulated as below.

### Table 8. Comparison of total parameters, trainable parameters, non-trainable parameters with thirty trainable layers.

| Total parameters | Trainable parameters | Non-trainable parameters |
|------------------|----------------------|--------------------------|
| 4,255,866        | 3,153,850            | 1,102,016                |

![Figure 17. Training loss, validation loss, training accuracy, validation accuracy of the data with thirty layers trainable layers.](image3)

![Figure 18. Confusion matrix of classification for the data with thirty trainable layers representing performance of the classification.](image4)
The eighth experiment consists all trainable parameters. In this experiment the network starts to learn from it’s own dataset. The summary of the results is tabulated as below.

Table 9. Comparison of total parameters, trainable parameters, non-trainable parameters with all trainable layers.

| Total parameters | Trainable parameters | Non-trainable parameters |
|------------------|----------------------|--------------------------|
| 4,255,866        | 4,233,978            | 1,102,016                |

Figure 19. Training loss, validation loss, training accuracy, validation accuracy of the data with all layers trainable layers.

Figure 20. Confusion matrix for the classification for the data with all trainable layers representing performance of the classification.

3. Conclusions and Future Researches

In this work an attempt is made to identify psoriasis affected skin area automatically using MobileNet machine learning model. In the initial stages of the experiment pretrained weights were used form ImageNet where the performance was not promising. As we start to introduce the trainable parameters the performance got better.

Table 10. Comparison of trainable parameters, sensitivity, specificity, precision and accuracy.

| Trainable Parameters | True Positive | False Negative | False Positive | True Negative | Sensitivity | Specificity | Precision | Accuracy |
|----------------------|---------------|----------------|----------------|---------------|-------------|-------------|-----------|----------|
| 0                    | 1             | 6              | 7              | 6             | 0.14        | 0.46        | 0.13      | 0.35     |
| 10,27,002            | 1             | 6              | 7              | 6             | 0.14        | 0.46        | 0.13      | 0.35     |
| 20,77,626            | 0             | 6              | 0              | 4             | 0.00        | 1.00        | Error     | 0.40     |
| 26,15,226            | 0             | 6              | 1              | 3             | 0.00        | 0.75        | 0.00      | 0.30     |
| 26,20,858            | 4             | 1              | 5              | 0             | 0.80        | 0.00        | 0.44      | 0.40     |
| 28,89,658            | 4             | 1              | 5              | 0             | 0.80        | 0.00        | 0.44      | 0.40     |
| 31,53,850            | 3             | 0              | 7              | 0             | 1.00        | 0.00        | 0.30      | 0.30     |
| 42,33,978            | 3             | 1              | 2              | 4             | 0.75        | 0.67        | 0.60      | 0.70     |

It is also observed that the model is not fully accurate as compared with dermatologists, but definitely acts as a tool in enabling the dermatologists to make better decisions in deciding the future course of treatment. The accuracy may be improved when NASNetLarge machine learning model is considered for the implementation, but compared to the size of NASNetLarge machine learning model, MobileNet is 22 times smaller than NASNetLarge.
The implementation of NASNetLarge machine learning model will considered in future work as it is considered as highly accurate machine learning model.

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