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RESEARCH ARTICLE

A Novel Light-Weight Approach for the Classification of Different Types of Psoriasis Disease Using Depth Wise Separable Convolution Neural Networks

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Abstract

Objectives: The main objective of the work is to classify the psoriasis affected skin into one of different psoriasis types viz. erythrodermic, gutatte, inverse, nail, plaque, and pustular using depth wise separable convolution neural networks. **Methods:** To identify the type of psoriasis disorder, the experiment uses MobileNet machine learning architecture which is based on depth-wise separable convolutions. In the preprocessing step, the input images are segmented into 224 pixels X 224 pixels with the help of the keras KerasImageDataGenerator function and in next step, these segmented images are fed as input to 28 layers of reconstructed MobileNet architecture. A series of convolutions and depth-wise separable convolutions layers are applied on the input images. The rectified linear activation function is applied to introduce non-linearity in the network. Adam optimizer algorithm is used for training the network. Categorical cross-entropy is used for the comparison of the accuracy of the experimental results with the existing work of classification of psoriasis disorder. **Findings:** Using MobileNet machine learning architecture, the experiments attained around 86% of classification efficiency, and an average F1− score of .94 as compared with VGG19 and ResNet-34, compared to the work done in[(1)]. **Novelty:** The novelty of the work lies in the prediction of the types of the psoriasis disorder accurately with less turnaround time with an accuracy of 86% consuming low processing capability which can be implemented on low powered hand-held devices.

Keywords: Machine Learning; Depth Wise Separable Convolution; Psoriasis Disorder; ReLU Activation; Pointwise convolutions

1 Introduction

Psoriasis is a skin disorder that is a resultant of immunity malfunctioning but the symptoms are reflected on the human skin. The disorder has a typical characteristic of a slightly raised skin surface from the surrounding skin which is extremely different from the rest of the unaffected skin. In some cases, the raised skin surface may be scaly. The raised skin can be easily visible and can be clearly distinguished from healthy skin. As all skin disorders can be cured easily if the diagnosis is done at the early stage of the disorder, classification of psoriasis skin disorders becomes an elementary step in the treatment of the disorder. There exist many types of psoriasis disorders and among them, erythrodermic psoriasis, gutatte psoriasis, inverse psoriasis, nail psoriasis, plaque psoriasis, and pustular psoriasis are considered in this work for the classification.

Li Peng et al.[(1)] reported a general classification diagnosis of psoriasis which used ResNet-34 which did not include any specific classification of types such as erythrodermic psoriasis, gutatte psoriasis, inverse psoriasis, nail psoriasis, plaque psoriasis, and pustular psoriasis which are considered in the current work for the classification. The authors calculated precision, recall, F1-score and ROC curve for the analysis of their results. The current work also calculates the same parameters for the comparison of the obtained results.

The use of ANN and CNN have gained momentum in the field of image processing over the traditional image processing methods as ANN and CNN proved to have high accuracy and less human intervention[(2)]. The use of ANN and CNN is preferred over traditional image processing techniques in the analysis of skin disorders mainly due the irregular shape, texture, internal color variations within a single disorder which are easily addressed by ANN and CNN and helps in diagnosis as reported earlier[(2)].

Yadav and Jadhav[(3)] did work on the classification of medical images of chest X-ray to classify bacterial and viral infection of the chest which used deep convolution neural network and attained the accuracy in the range of 80-90, where the images were in black and white with only two channels where as our current work in this paper includes color images of psoriasis with three color channels.

In[(4)] deployed convolutions neural network to classify and identify plaque and gutatte psoriasis of the skin in which they worked 82 plaque and 105 gutatte psoriases with an accuracy of 82.9 for plaque and 72.4 gutatte psoriases. They segmented the input images into 160 x 160 pixels before feeding the images to the convolutions neural network. As the authors only considered only two types of classes, there remains the scope for the classification of additional types of psoriasis disorders.

In[(5)] examined many machine learning applications in the evaluation and management of psoriasis. The authors considered four open source online available recourses from MEDLINE, Google Scholar, ACM Digital Library, and IEEE Xplore which showed that cardiovascular disease and diabetes are the comorbidities which are predominantly observed in psoriasis affected patients. This is the first exhaustive study which presents the relations ships between cardiovascular disease, diabetes and psoriasis.

In[(6)] worked on erythemato squamous disease which was mainly attributed to genetic and environmental factors. The author employed auto encoders and deep neural networks to catalog erythemato squamous disease into six classes. The author also claim that this is the first study of its kind to use auto encoders and deep neural networks to study erythemato squamous disease.

In[(7)] studied around 45 works in classification and identification common skin disorders using deep learning methods. They also observed in their study that combination of many different models provided better accuracy and performance in the classification and identification common skin disorders.

In[(8)] studied transfer learning and proposed their own neural network for the analysis of breast cancer diagnosis which eliminated the distance disparity between source data and target data which is known to have over fitting results particularly in the case of limited data in the area of skin disorders.

In[(9)], worked on early detection of melanoma with a minimal data set on case based system by deploying deep convolution neural networks. Their work observed convolution neural networks will help in early detection of malignant melanoma. They also observed that fine tuning their model would lead to better accuracy and performance.

2 Methodology

The database of psoriasis is built by three sources which include the Department of Skin and STD, Karnataka Institute of Medical Sciences, Hubli and Department of Dermatology, Navodaya Medical College, Raichur and Rani Channamma University, Belagavi from where psoriasis images are collected. Around 8000 images are collected from the three sources. As the work includes machine learning models, no cleaning of the images is carried out as it leads to the loss of pixels. One of the primary goals of the experiment is the include all the pixels in the classification of the psoriasis disorder.

In the experiment, we have used around 6400 images during the training phase, which consists of 748 images of erythrodermic psoriasis, 960 images of gutatte psoriasis, 936 images of inverse psoriasis, 2352 images of nail psoriasis, 1032

images of plaque psoriasis, and 372 images of pustular psoriasis images. The test and validation set contains around 2000 images in combination of all six disorders. The input folder structure is shown in Figure 1.

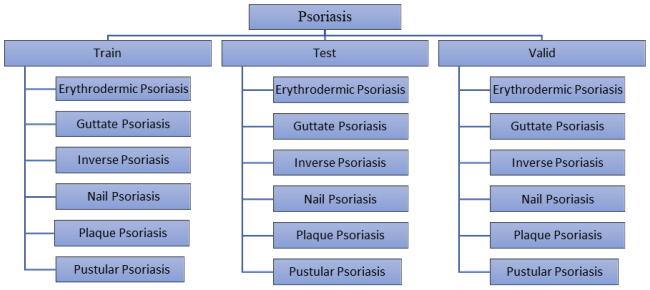

Fig 1. Input folders structures for the experiment

As MobileNets accepts the input size of the image to be 224 X 224 pixels, all the 6400 input images are segmented first before the actual processing into 224 X 224 pixels which can be regarded as pre-processing. Then they are feed to the input layer of MobileNets where the actual processing takes place. The various layers involved in the processing are shown in Figure 2 and Figure 3.

Depthwise Convolution
Batch Normalization
ReLU
Convolution
Batch Normalization
ReLU

Fig 2. Depthwise convolution block architecture

Input Layer
Zero Padding
Convolution
Batch Normalization
ReLU
Depthwise Convolution Block – 1
ZeroPadding
Depthwise Convolution Block – 2
Depthwise Convolution Block – 3
ZeroPadding
Depthwise Convolution Block – 4
Depthwise Convolution Block – 5
ZeroPadding
Depthwise Convolution Block – 6
Depthwise Convolution Block – 13
Global Average Pooling
Reshape
Dropout
Convolution Preds
Reshape
Activation
Output Layer

Fig 3. MobileNet architecture used

3 Results and Discussions

Compared to all the other existing works [1–4], the presented work contains six classes for the classification of psoriasis and the use of machine learning model proved to be beneficial where no pixels in the input images are lost in comparison of principal component analysis method and support vector machines and require human intervention and have less accuracy. As discussed in the previous section, in the first instance the model is fed with input images with the pre-trained weights from ImageNet. The training loss, validation loss, training accuracy, and validation accuracy are shown in Figure 4 In [1] used ResNet-34 for the general classification in the diagnosis of psoriasis which consumes 83MB of space and attained the F1- score between .8 to .9 where as our experimental work used MobileNet to classify six types of psoriasis which are of only of 16MB in size and achieved an F1 score of .94 which is much improvised compared to the work done by Li Peng, Yi Na, Ding Changsong, L I Sheng and Min Hui.

Table 1. Summary of parameters with pre-determined weights

Total weights	Trainable weights	Non-trainable weights
3,235,014	0	3,235,014

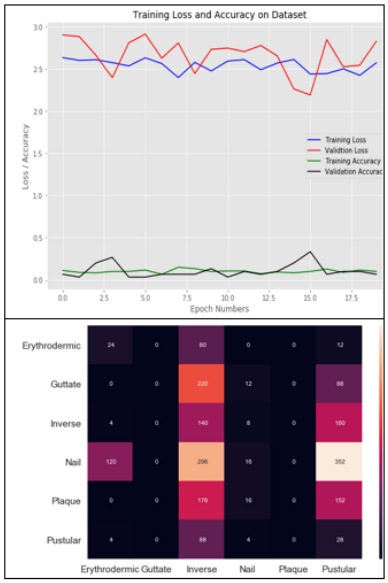

Fig 4. Training loss, validation loss, training accuracy, validation accuracy of the classification with pre-determined weights, and Confusion Matrix with pre-determined weights

Table 2. Summary of parameters with five trainable layers

Total weights	Trainable weights	Non-trainable weights
3,235,014	1,056,774	2,178,240

Table 3. Summary of parameters with ten trainable layers

Total weights	Trainable weights	Non-trainable weights
3,235,014	1,070,086	2,164,928

In a comparison of the work of Yadav and Jadhav [3], where they considered only X-ray images which include only black and white channels for the classification of bacterial infection and viral infection of the chest and attained an accuracy of 80-90 %, our method considers the real-world color images of psoriasis images and classify with an accuracy of 95% even after considering three color channels.

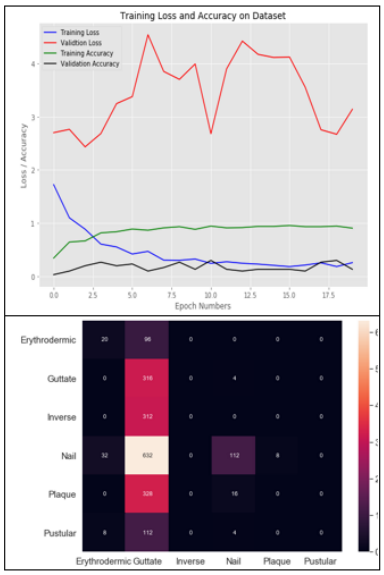

Fig 5. Training loss, validation loss, training accuracy, validation accuracy with five trainable layers, and Confusion Matrix with five trainable layers

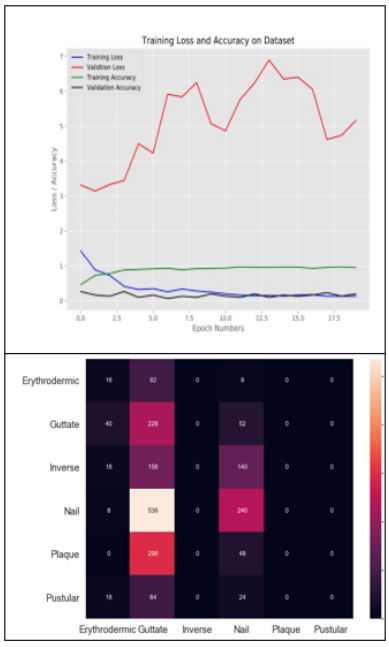

Fig 6. Training loss, validation loss, training accuracy, validation accuracy with ten trainable layers, and Confusion Matrix with ten trainable layers

Table 4. Summary of parameters with fifteen trainable layers

Total weights	Trainable weights	Non-trainable weights
3,235,014	1,600,006	1,635,008

Table 5. Summary of parameters with twenty trainable layers

Total weights	Trainable weights	Non-trainable weights
3,235,014	1,864,198	1,370,816

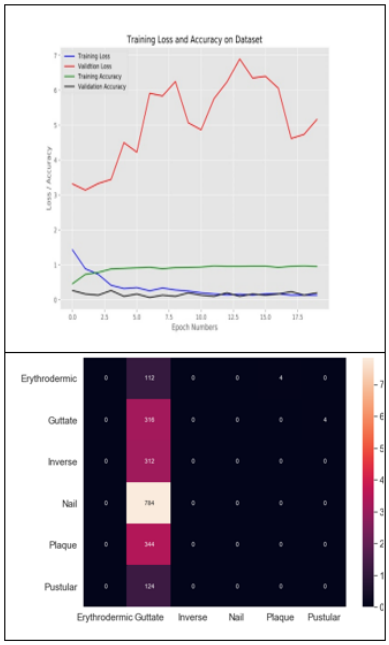

Fig 7. Training loss, validation loss, training accuracy, validation accuracy with fifteen trainable layers, and Confusion Matrix with fifteen trainable layers

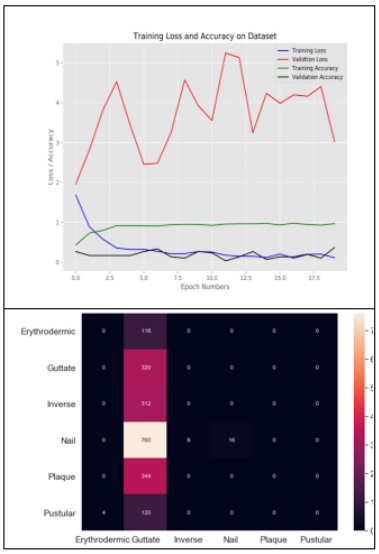

Fig 8. Confusion Matrix with twenty trainable layers and Training loss, validation loss, training accuracy, validation accuracy with twenty layers

Table 6. Summary of parameters with twenty-five trainable layers

Total weights	Trainable weights	Non-trainable weights
3,235,014	2,131,974	1,103,040

Table 7. Summary of parameters with thirty trainable layers

Total weights	Trainable weights	Non-trainable weights
3,235,014	2,131,974	1,103,040

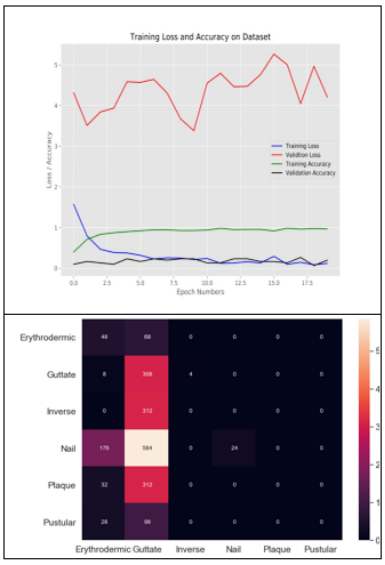

Fig 9. Training loss, validation loss, training accuracy, validation accuracy with twenty-five trainable layers, and Confusion Matrix with twenty-five trainable layers

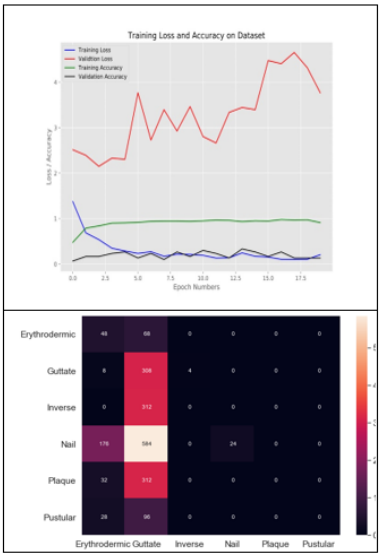

Fig 10. Training loss, validation loss, training accuracy, validation accuracy with thirty trainable layers, and Confusion Matrix with thirty trainable layers

Table 8. Summary of parameters with all trainable layers

Total weights	Trainable weights	Non-trainable weights
3,235,014	3,213,126	21,888

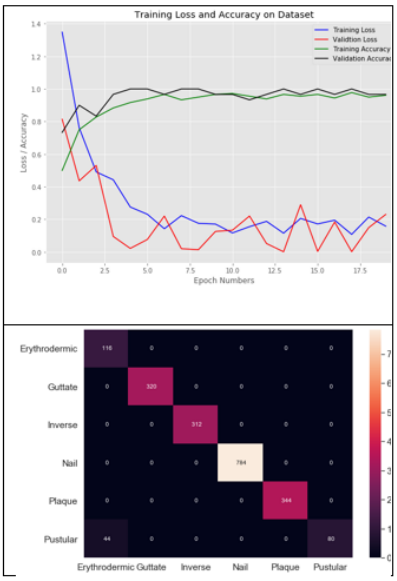

Fig 11. Training loss, validation loss, training accuracy, validation accuracy with all trainable layers, and Confusion Matrix with all trainable layers

Table 9. Summary of accuracy and precision with all trainable layers

Sample Group Details	Sample Group	Precision	Recall	F1-score	Support
Erythrodermic psoriasis	0	0.72	1	0.84	116
Gutatte psoriasis	1	1	1	1	320
Inverse psoriasis	2	1	1	1	312
Nail psoriasis	3	1	1	1	784
Plaque psoriasis	4	1	1	1	344
Pustular psoriasis	5	1	0.65	0.78	124
	Accuracy			0.98	2000
Macro	Average	0.95	0.94	0.94	2000
Weighted	Average	0.98	0.98	0.98	2000

In [4] used only convolutions neural network and classified only plaque and gutatte psoriasis, and achieved an individual accuracy of 82.9 for plaque and 72.4 gutatte psoriases, while the current work considered erythrodermic psoriasis, gutatte psoriasis, inverse psoriasis, nail psoriasis, plaque psoriasis, and pustular psoriasis and achieved a classification efficiency of 95%.

4 Conclusions and Future Researches

The authors considered the existing methods in classification and identification [1,3,4] of skin disorders and identification of the type of psoriasis will help dermatologists in treating the patients with accuracy. The work achieved an accuracy of 95% which is certainly an improvement compared to earlier work of classification and identification [1,3,4] of skin

It is observed that the performance of identification of erythrodermic psoriasis, gutatte psoriasis, inverse psoriasis, nail psoriasis, plaque psoriasis and pustular psoriasis using MobileNet machine learning algorithm on the collected data set was not promising at the earlier stages of the training.

As new parameters were updated from the data set, the performance of classification started to improve. During the last set of experiments, all the layers of the network are made to learn from the training data itself and the accuracy of 95% is achieved in comparison with many machine learning models, which need high processing power compared to the MobileNet machine learning algorithm and have high latency period. The work can be still more refined with larger data sets and can be fine-tuned

with an additional number of layers.

Most of the work in the skin diseases identification and classification including the work of[10], used the standard data set of ISIC 2018. As a future scope of the work, the authors will deploy the methodology on ISIC 2018 data set which will help in getting more insights about accuracy and performance.

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