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RESEARCH ARTICLE

A Machine Learning Approach for the Estimation of Severity of Psoriasis Disorder Using Depth-Wise Convolution Neural Network

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Abstract

Objectives: To design and develop a computer-aided tool for the estimation of the severity of psoriasis-affected skin areas using depth-wise convolution neural networks. **Methods:** The experiment consists of 5951 input images which are divided into a training set, validation set, and testing set. The training set consists of 2282 mild images, 646 moderately affected images, and 323 severely affected psoriasis images. The validation set consists of 600 mild, moderate, and severely affected images in each category. The testing set consists of 200 mild, moderate, and severely affected images in each category. The reconstructed MobileNet machine learning model is used in the estimation of severity. The reason for using the reconstructed MobileNet machine learning model is the less turnaround time required in the estimation of severity and the use of depth-wise convolution layers around which the model is built, which can be implemented in low-power, low-memory handheld devices. At the initial stages, pre-trained weights of ImageNet are used and at a later stage of the experiment, the network learns from our input data set. **Findings:** The experimental results proved to be significant and accurate when verified with the dermatologists. The fully trained network on the input data set is found to predict the severity around 90% which is counter-verified by the dermatologists. At the beginning of the experiments, when the neural network was run on the data set with the weights from ImageNet, the estimate of the disorder was not convincing. As the neural network was trained and weights were recalculated based on our collected data set, the results got improved. Even though MobileNet machine learning model was used, the average turnaround time for 20 epochs was about 27 minutes, which is a significant part of the experiment in developing the tool. An average F1 score of .94 is achieved when all the layers of the network are trained. **Novelty:** The novelty of the work lies in the prediction of the types of the severity psoriasis disorder accurately with less turnaround time with an accuracy of 90% where the results are cross verified by dermatologists and the tool can

be implemented on low-powered, low-processing hand-held devices.

Keywords: Psoriasis; Depthwise convolution neural network; Machine Learning; Keras; Skin Texture

1 Introduction

Psoriasis is an autoimmune disorder that has implications on the skin's surface. Assessment of the condition of the skin becomes a priority task in the line of treatment of the disorder. The assessment becomes subjective due to many environmental conditions, but the need is to access the patient's situation subjectively without getting affected by the environmental conditions.

Psoriasis and other skin diseases are significant disorders affecting people at any age and geographies[(1)]. People with dermatological disorders have a higher risk for various mental comorbidities (e.g., anxiety, depression, etc). Particularly, people with facial dermatological diseases such as psoriasis are living with serious physiological and sociological problems[(2,3)]. For instance, a high risk of suicide attempts and suicidal death of people with psoriasis disease in Quebec has been shown in a recent study[(3)]. Traditional diagnosis of skin diseases and psoriasis is based on visual examinations of lesions by a dermatologist. Therefore, computer-assisted diagnosis for these diseases with pattern recognition can be performed to provide objective, accurate, and early diagnosis in dermatology.

In this paper MobileNet machine learning model, a machine learning model is used to access the state of the skin and to decide the course of action for the treatment. The estimation of severity is built on the basic idea of the difference in the color variation that exists between mild, moderate, and severely affected psoriasis affected skin. The paper is based on the RGB color model which implies that all the images are constructed using basic red, blue, and green channels. As we observe the images of psoriasis-affected people, the normal skin contains less number of red pixels as we compare the redness content of the images, the frequencies of red pixels increase from mild to moderate and to severe. The same variation is also observed concerning the diversity of white pixels. The work includes the MobileNet machine learning model to categorically classify the disorder into mild, moderate, and severe.

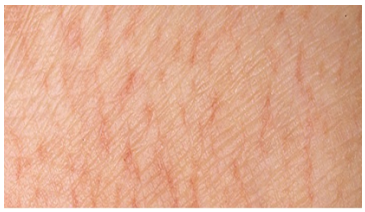

Fig 1. Image of healthy normal skin

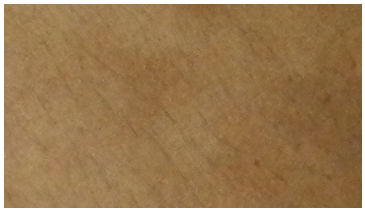

Fig 2. Image of psoriasis-affected skin in mild cases

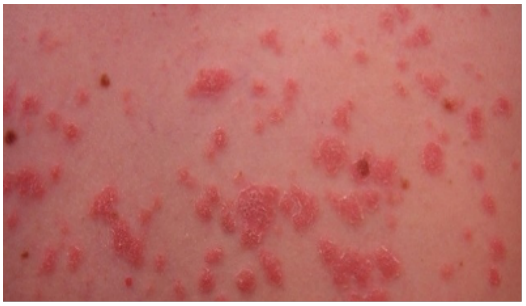

Fig 3. Image of psoriasis-affected skin in moderate cases

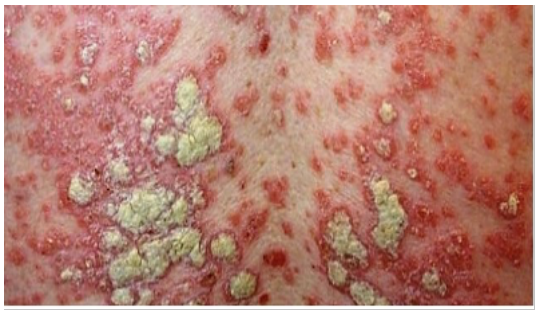

Fig 4. Image of psoriasis-affected skin in severe cases

The authors in [1] reported their work on a general classification to use depth-wise separable convolution neural networks to put psoriasis-affected skin into one of six different types: erythrodermic, guttate, inverse, nail, plaque, and pustular. Based on depth-wise separable convolutions, their experiment employs MobileNet machine learning model to determine the type of psoriasis disorder in the experiment. Before reconstruction, the input images are segmented by the KerasImageDataGenerator function into 224 x 224-pixel squares, which are then fed into the 28 layers of the reconstructed MobileNet machine learning model architecture in the next step. The input images are subjected to a sequence of convolutions and depth-separable convolutions layers. Applying a rectified linear activation function creates non-linearity in the network. The network is trained using the adam optimizer method. A comparison of experimental results with prior work on psoriasis disorder classification is done using categorical cross-entropy. But the work does not analyse the severity of psoriasis whereas it only classifies the type of psoriasis.

The authors in [4] also worked on five forms of psoriasis - plaque, guttate, inverted, pustular, and erythrodermic and classified them using a deep learning approach. The application of CNN presented an accuracy of 84.2% and that of LSTM presented 72.3%. Implications of this work demonstrate the potential of deep learning applications to be applied to other areas of dermatology for better prediction and analysis of skin disorders. This work also emphasizes on the identification of the type of forms of psoriasis rather than the severity of psoriasis.

The authors in [2] noted efficient methods developed with deep learning in the last ten years have provided objectivity and high accuracy in the diagnosis of skin diseases. It is not possible to run deep networks on resource-constrained devices such as mobile phones. Therefore, lightweight network architectures have been proposed in [2] the work. Their results indicated a diagnosis of skin diseases with 94.76% accuracy, which is a general case of dermatology.

The authors in [3] used an unsupervised method to identify cell clusters of memory based on computer programs that use neural networks. Patients with psoriasis had a distinct distribution of memory T cells. Most patients with psoriatic arthritis have psoriasis before they have arthritis. Most patients with PsA have a progressive form of the disease if the diagnosis is correct. All models for the transition from psoriasis to PsA were proposed and concluded that in the body when the immune system isn't working properly a critical element in the process of change can initiate psoriasis. Den Braanker et al [3] worked on the relationships that exist among psoriasis and memory T cells but the work carried out in this research paper estimates the severity among different classes of psoriasis.

The authors in [5] a total of 33 research papers survey and grouped according to the topic and then synthesized into evaluation or management articles that covered five different types of content: Images of the skin can be used to evaluate (A) (1) psoriasis

lesions, (2) lesion segmentation, and (3) lesion severity and area score; (B) clinical management: (1) prediction of complications, and (2) treatment of problems. They concluded that it is possible to use machine learning to help diagnose and treat psoriasis. Current psoriasis-related ML research focuses on medical image analysis, predicting problems, and discovering new treatments. When it comes to ML breakthroughs, dermatologists need to be aware of how the technology can assist them to make better decisions and assessments for their patients but the paper did not touch upon the classification of severity.

The authors in [6] worked on erythematous squamous disease which was mainly attributed to genetic and environmental factors. The author employed autoencoders and deep neural networks to catalog erythematous squamous disease into six classes. The author also claims that this is the first study of its kind to use autoencoders and deep neural networks to study erythema squamous disease, But the autoencoders were not employed to access the severity of psoriasis.

The authors in [7] studied around 45 works in the classification and identification of common skin disorders using deep learning methods. They also observed in their study that a combination of many different models provided better accuracy and performance in the classification and identification of common skin disorders, but severity assessment was not taken care of.

The authors in [8] studied transfer learning and proposed their 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 overfitting results, particularly in the case of limited data in the area of skin disorders.

The authors in [9] worked on the 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 the early detection of malignant melanoma. They also observed that fine-tuning their model would lead to better accuracy and performance.

From the above study, we understand that similar work is in progress in the field of psoriasis which makes use of machine learning. It is observed that literature also reveals that similar work is done in [1], but the work only identifies the type of psoriasis but does not estimate the severity so the current work reported can be complementary to the work done in [1]. Work in [4] also deals with classification in authors have reported an accuracy of 84.2% by CNN and that of LSTM presented 72.3%, it further does not investigate the severity of psoriasis, whereas work reported in this paper can take the inputs from [4] and further estimate the severity of psoriasis where the current work acts as the enhancement of work done in [4]. In [2] work is reported about the diagnosis of skin diseases with high accuracy where the requirement of the high processing power of computers is evident which can in turn delay the time required for the results which are disadvantageous in the medical field where decisions are made quickly to stop the patients from suffering. The work reported in this paper uses CNN and reconstructed MobileNet machine learning model which requires less processing infrastructure and also consumes less memory which can be implemented in handheld devices the turnaround time is also less which is an added advantage for the dermatologist where the results can be used as a second opinion.

2 Methodology

The estimation of the severity of psoriasis disorder using a depth-wise convolution neural network is implemented using the MobileNet machine learning model which contains, a convolution layer, zero padding layer, and batch normalization layers. A convolution layer is a simplified form of operating the masks on the input images, but the basic difference being the values of the mask keep changing every time during the execution of each epoch of the neural network which makes the process intelligent. The images are collected from the Department of Dermatology, KIMS, Hubli, Karnataka, India, and Navodaya Medical College, Raichur, Karnataka, India. For training purposes, images from the internet are also used but images collected from the internet are not used for validation and testing purposes, as it is observed that the images on the internet are found to be enhanced, and altered using various image processing tools as it can alter the predictions in the real-time scenario. The arrangement of the folders is as shown below.

The experiment consists of 5951 input images which are divided into a training set, validation set, and testing set. The training set consists of 2282 mild images, 646 moderately affected images, and 323 severely affected psoriasis images. The validation set consists of 600 mild, moderate, and severely affected images in each category. The testing set consists of 200 mild, moderate, and severely affected images in each category.

The architecture of the MobileNet machine learning model contains a convolution layer, zero Padding layer, batch Normalization layer, ReLU layer, and blocks of depthwise convolutions. The convolution layer is similar to that of the kernel which is used in image processing techniques, but a basic difference is that the coefficients of the kernel remain constant in image processing while the coefficients keep changing on every epoch of the network. A zero padding layer is used to preserve all the bits of the information present in the input images which tends to lose when convolution is applied. The zero padding layer is padding the input image under consideration with zeros to preserve the information which eliminates the shrinking of input images. The batch normalization layer is used to normalize the input pixel values which have huge differences among them. This layer brings all the input values to a new normalized scale. The ReLU layer is the activation which will convert all the

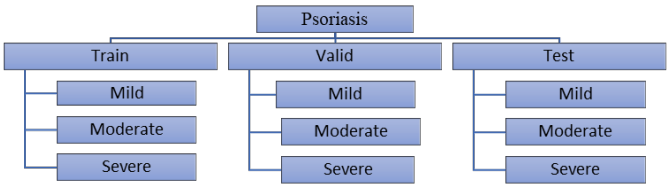

Fig 5. Structure of arrangements of folders

negative values to zero and positive values will remain as it is. The experiment is carried out on an Intel Core i5, 8th Generation processor configured with 16GB RAM. The work includes Python language with version 3.7.6, Jupyter Notebook, and libraries include Keras and TensorFlow frameworks. The input images need to be divided into 224 X 224 which is the input size required by the MobileNet machine learning model which is similar to the pre-processing step employed in traditional image processing workflows. In the initial stage of the experiment, pre-determined weights from the ImageNet are used. At the later stage of the experiment, the layers are eventually made trainable which means the neural network starts to learn from the input images, as a result, the weights get updated during each epoch. The arrangement of various layers of the MobileNet machine learning model architecture used is shown in Figure 7.

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 6. The architecture of depth-wise convolution block used

The model contains 13 depth-wise convolution blocks which in turn contain layers such as depth-wise convolution, batch normalization, ReLU, normal convolution, batch normalization, and ReLU in sequence. The architecture of the depth-wise convolution block is shown in Figure 6.

Various aspects in such as age, severity, and stress levels are considered in deciding the modes of treatment of psoriasis. The methods used by dermatologists used currently in treating psoriasis are outlined below.

Algorithm for treating if the candidate is below 18 years.

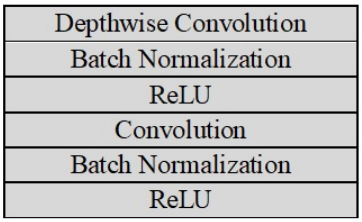

Fig 7. The architecture of the model used

Step 1. Verify if the age of the patient is less than the age of 18 years.
Step 2. Is the kid ready for treatment such as local applications?
Step 3. Is psoriasis predominantly mild guttate psoriasis?
Step 4. The application of purified coal tar is recommended.
Step 5. Exposure to sunlight for 15 minutes daily during the mornings and in the evenings is recommended.
Algorithm for treating patients who are above the age of 18 years.
Step 1. Is the person ready to treat on his own at home?
Step 2. If the body is covered with mild or moderate flakes or scales.
Step 3. If steps 1 and step 2 are true, local application of coal tar is recommended.
Step 4. If step 3 is not adoptable, lower levels of steroids are recommended.
Step 5. If steps 1 and step 2 are false, hospitalization is needed and treated with salicylic acid and coal tar.
The algorithm is used in treating patients with severe conditions with high amounts of discharge of flakes.
Step 1. Analysis of the severity is carried out with the candle wax method.
Step 2. Verification of the flakes being discharged on daily basis.
Step 3. Study of the patient to check if one has undergone any type of treatment.
If so, then the previous mode of treatment need not be repeated.
Step 4. Verify if the patient is diagnosed with skin cancer.
Step 5. Verify if the patient is diagnosed with hypertension.
Step 6. Verify if the patient is diagnosed with renal-related issues.
Step 7. If steps 4, step 5, and step 6 are false, then
local application of salicylic acid is recommended.
Step 8. In certain conditions, based on the progress local application of mineral oil is also recommended.
Step 9. Local application of purified coal tar is also recommended.
Step 10. If steps 4, step 5, and step 6 are found to be true, then further investigations are needed to decide the future course of treatment.

The above example is predominantly, based on the current condition of the patient. Hence analysis of the current situation becomes critical in the line of the treatment.

3 Results and Discussion

In the first set of experiments, predetermined weights of ImageNet are used and the below table summarizes the number of parameters used.

Table 1. Summary of parameters used during the initial set of experiments

Total parameters of the experiment	Trainable parameters of the experiment	Non-trainable parameters of the experiment
3,235,014	0	3,235,014

Table 2. Summary of parameters used during five trainable layers

Total parameters of the experiment	Trainable parameters of the experiment	Non-trainable parameters of the experiment
3,235,014	1,056,774	2,178,240

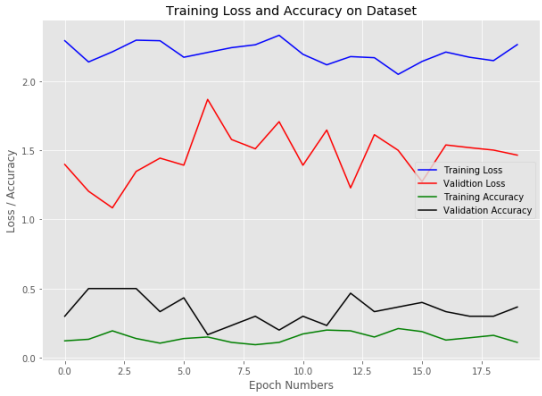

Fig 8. Graph of training loss, training accuracy, validation loss, and validation accuracy without trainable parameters

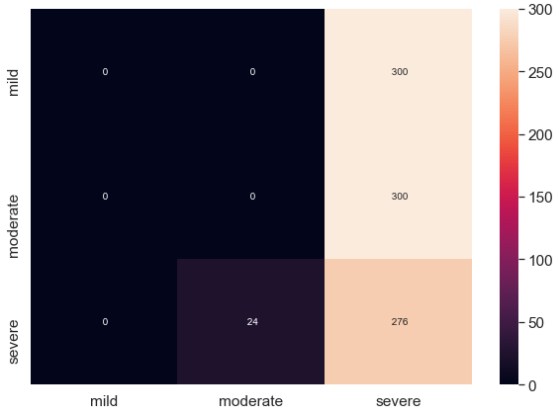

Fig 9. Accuracy of predictions of mild, moderate, and severe conditions during the initial stage of the experiment without any trainable parameters

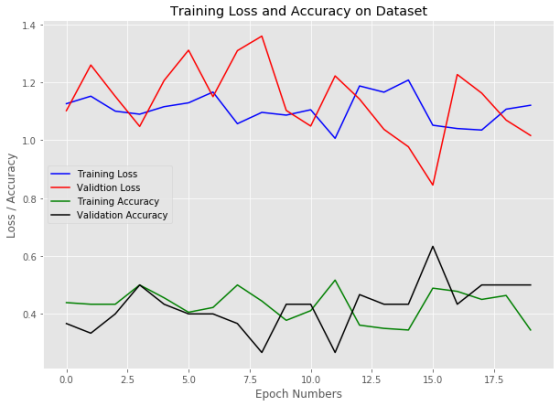

Fig 10. Graph of training loss, training accuracy, validation loss, and validation accuracy with five trainable parameters

4 Conclusion

Various severity classification schemes exist, but none have reached an agreement or provide a clear delineation between mild, moderate, and severe variants. Currently, psoriasis classifications are based mainly on consensus. The existing gold standards

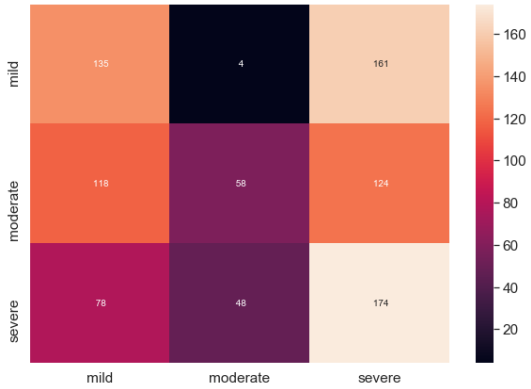

Fig 11. Accuracyof predictions of mild, moderate, and severe conditions with five trainablelayer parameters

Table 3. Summary of parameters used during ten trainable layers

Total parameters of the experiment	Trainable parameters of the experiment	Non-trainable parameters of the experiment
3,235,014	1,070,086	2,164,928

Table 4. Summary of parameters used during fifteen trainable layers

Total parameters of the experiment	Trainable parameters of the experiment	Non-trainable parameters of the experiment
3,235,014	1,600,006	1,635,008

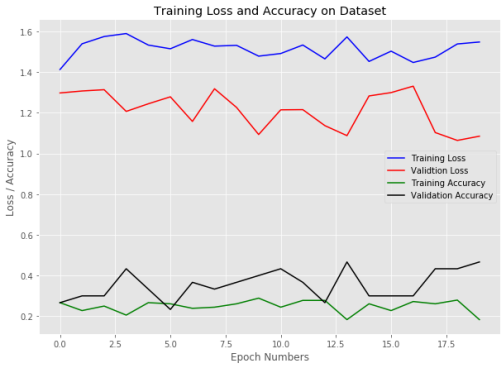

Fig 12. Graph of training loss, training accuracy, validation loss, and validation accuracy with ten trainable layer parameters

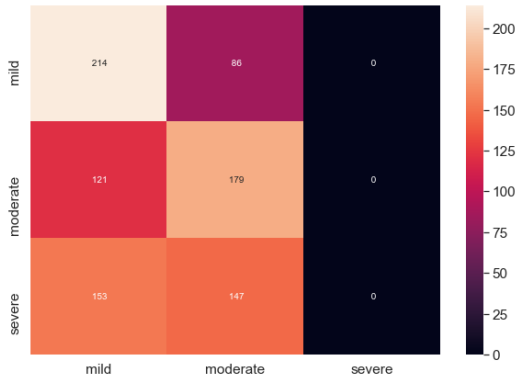

Fig 13. Graph of training loss, training accuracy, validation loss, and validation accuracy with fifteen trainable layer parameters. Accuracy of predictions of mild, moderate, and severe conditions duringthe initial stage of the experiment with ten trainable layer parameters

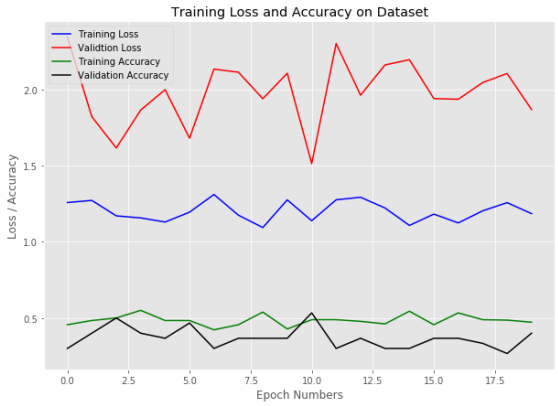

Fig 14. Graph of training loss, training accuracy, validation loss, and validation accuracy with fifteen trainable layer parameters

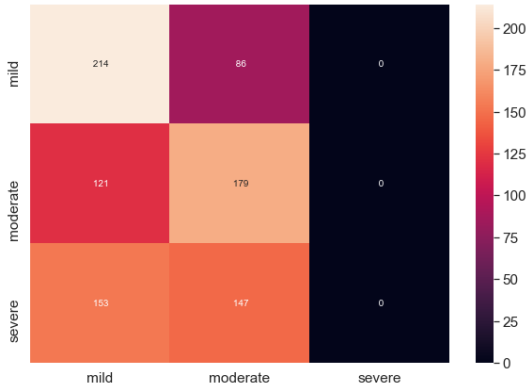

Fig 15. Accuracyof predictions of mild, moderate, and severe conditions during the initialstage of the experiment with fifteen trainable layer parameters

Table 5. Summary of parameters used during twenty trainable layers

Total parameters of the experiment	Trainable parameters of the experiment	Non-trainable parameters of the experiment
3,235,014	1,864,198	1,370,816

Table 6. Summary of parameters used during twenty-five trainable layers

Total parameters of the experiment	Trainable parameters of the experiment	Non-trainable parameters of the experiment
3,235,014	2,131,974	1,103,040

Fig 16. Graph of training loss, training accuracy, validation loss, and validation accuracy with twenty trainable layer parameters

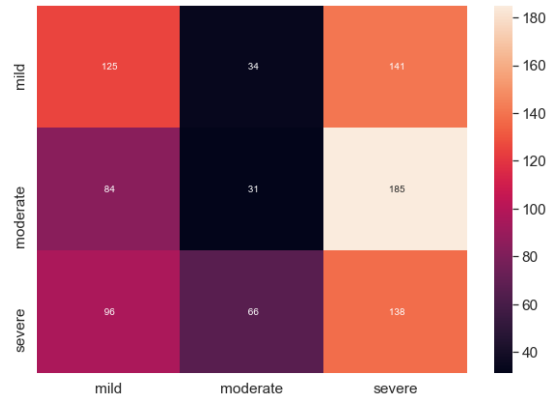

Fig 17. Accuracy of predictions of mild, moderate, and severe conditions during the initial stage of the experiment with twenty trainable layer parameters

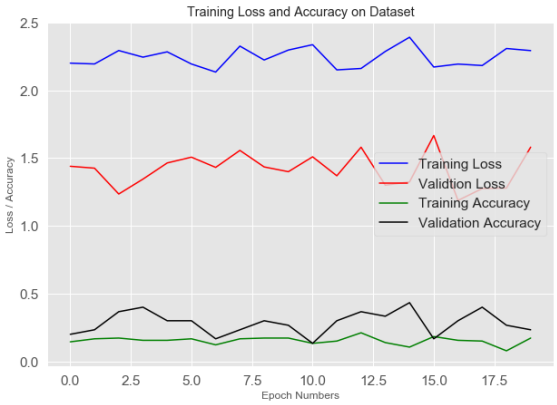

Fig 18. Graph of training loss, training accuracy, validation loss, and validation accuracy with twenty-five trainable layer parameters

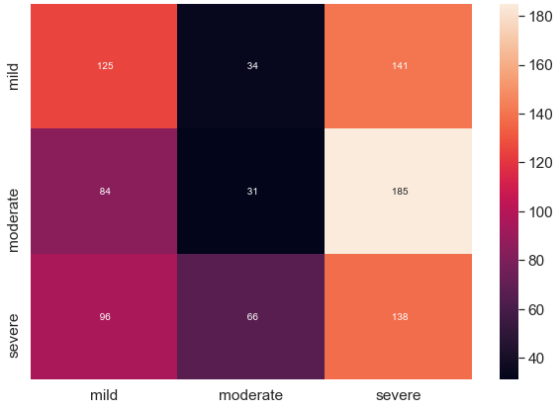

Fig 19. Accuracyof predictions of mild, moderate, and severe conditions of the experiment withtwenty-five trainable layer parameters

Table 7. Summary of parameters used during thirty trainable layers

Total parameters of the experiment	Trainable parameters of the experiment	Non-trainable parameters of the experiment
3,235,014	2,131,974	1,103,040

Table 8. Summary of parameters used during thirty-five trainable layers

Total parameters of the experiment	Trainable parameters of the experiment	Non-trainable parameters of the experiment
Total parameters of the experiment.	Trainable parameters of the experiment.	Non-trainable parameters of the experiment.

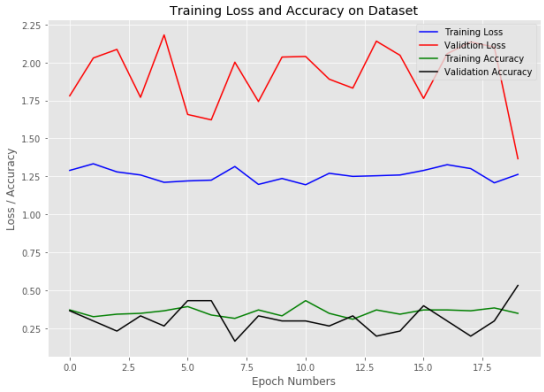

Fig 20. Graph of training loss, training accuracy, validation loss, and validation accuracy with thirty trainable layer parameters

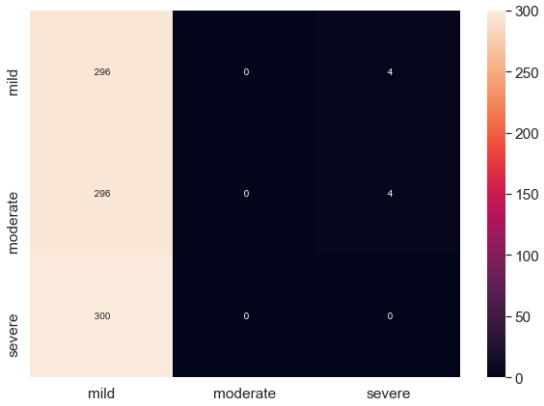

Fig 21. Accuracy of predictions of mild, moderate, and severeconditions of the experiment with thirty trainable layer parameters

Fig 22. Graph of training loss, training accuracy, validation loss, and validation accuracy with thirty-five trainable layer parameters

Table 9. Summary of parameters used during all trainable layers

Total parameters of the experiment	Trainable parameters of the experiment	Non-trainable parameters of the experiment
3,235,014	3,213,126	21,888

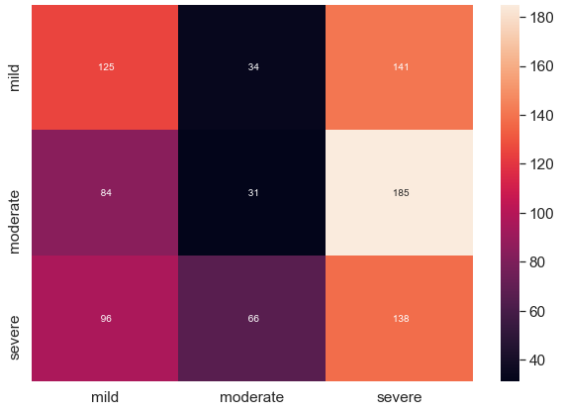

Fig 23. Accuracy of predictions of mild, moderate, and severe conditions of the experiment with thirty-five trainable layer parameters

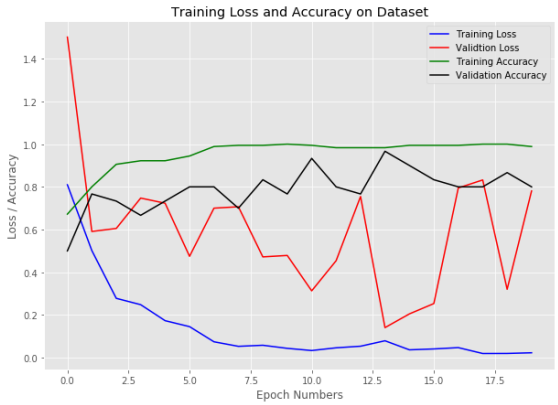

Fig 24. Graph of training loss, training accuracy, validation loss, and validation accuracy with all trainable layer parameters

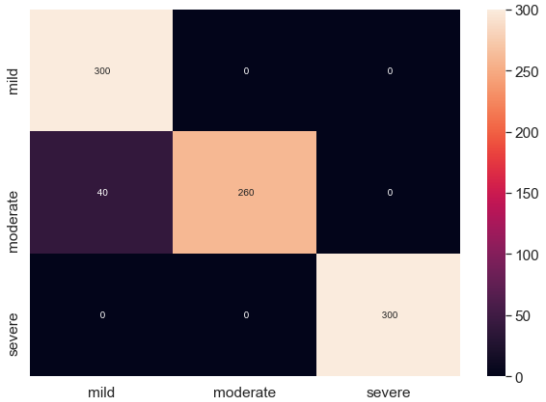

Fig 25. Accuracy of predictions of mild, moderate, and severe conditions with all trainable layer parameters

for the classifications of severity include the combined use of PASI, BSA, and sPGA which are manually carried out, and then the results are combined for the estimations. The presented work in the paper is fully automated and the accuracy will increase if the input data set is increased. The approach followed provided promising results. At the initial stages of the experiments, when the neural network was operated on the data set with the weights on ImageNet, the estimation of the disorder was not convincing. Gradually as the neural network was trained and the weights got updated, the results were promising. Even though MobileNet machine learning model was used, the average turnaround time for 20 epochs was around 27 minutes which is the concern raised by the dermatologists. It is observed that the work on improvement of the turnaround time can be considered in the future scope of the function. During requirements analysis, it was found that it was impossible to diagnose and estimate the severity of all images in the dataset for each class is difficult. Similarly, extreme cases were excluded from the concerned area since they are easy to estimate. Developing a lightweight application with a CNN Model was the best solution. This study found MobileNet with transfer learning to be the best model for automatic skin disease diagnosis. While converting a trained model to the model to fit the data, it is observed that some of the necessary data is lost. More training and data may help with this. Capturing large photographs increases the accuracy of detecting severity. Future research should focus on increasing the dataset and developing more accurate models to estimate the severity. As an extension of this study, the performance of the proposed method can be compared with the performance of a capsule network-based method since capsule networks can preserve spatial relationships of learned features and have been proposed recently for image classification. It is commonly known that deep neural networks are data-hungry and various augmentation techniques in general have been used to solve different problems with deep networks and to improve the reliability and robustness of the methods. Therefore, the proposed method can be tested with the increased number of images as an extension of this work. An important advantage of the proposed approach is that it does not need an extra normalization stage, such as in [1,4], which increases computational complexity.

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