# Framework Development for Detection of Skin Diseases Using Advanced Deep Learning Models and Suggestion of Pharmaceutical Remedy Products

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## Abstract

Skin diseases are quite common in the present times and majority of the world population is facing these in some form or the other. However, inherent social stigma, attached to skin-related issues specially in the third world countries restricts people from seeking appropriate help from dermatologists unless the issues goes out of proportion. Several researches have been conducted on detection of skin related issues using Artificial Intelligence, however, no proper framework has been developed on how the use of these advanced technologies can directly help the affected individuals. The current work uses advanced models like CNN and Inception V3 models which perform better in terms of detecting cases of skin ailments from images and also suggest a framework through which proper information can be presented to the affected individuals and support them to take proper remedy by automatically suggesting one. This work is an effort to conglomerate the power of deep learning in the detection of skin related issues with the application of proper pharmaceutical products in the form of remedies for skin disease. This work unravels the path for practical application of deep learning algorithms for proper use of pharmaceutical products for benefits of patients.

*Keywords :* CNN, Deep Learning Application, dermatology, pharmaceutical products, skin disease

## I. INTRODUCTION

Dermatology is one of the most challenging subjects to do medical diagnosis because of its inherent intricacies [1]. Different diseases resulting in unhealthy skin conditions are quite prevalent in every area of the globe. Even though it is somewhat a common condition, it is extremely difficult to diagnose and needs much previous training in the appropriate field. According to Rajadurai, Vidhya, Ramya, and Bhaskar [2], the prevalence of skin diseases worldwide indicates that the market for skin care products and ointments is enormous. The entire size of the worldwide market for skin care products in 2018 was expected to be \$134.80 billion according to industry specific research data. Between 2019 and 2025, it is anticipated that the market for skin care products will grow at a pace of 4.4% per year. It is anticipated that the market would be boosted in the future by the rising demand for skin care products such as ointments.

There have been several studies on the use of Machine Learning methods for dermatology. On the basis of images, a range of deep learning models capable of recognising the kind of skin disorder have been constructed [3, 4]. The present study is an effort to extend prior concepts by offering a more complex and accurate model and by suggesting a mechanism by which skin care items (skin ointment as a therapy) might be automatically suggested to a user who uploads a picture of a skin condition requiring treatment. The present study proposes a model in the said direction. In some countries of the globe, seeing a dermatologist for treatment of a skin condition is still uncommon, and skin problems are often seen as social taboo. Due to the social stigma that exists in various countries of the globe on skin related problems,

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patients have a propensity to keep their illness to themselves and do not want to contact a medical expert. Unless the skin condition is widespread hampering day to day activities, the patient does not desire to schedule an appointment with the dermatologist. In addition to this scenario, there are cases where the patients themselves have been anxious about visiting the pharmacy and selecting the correct therapy for some skin disorders, such as those associated with ageing and others. However, there is limited knowledge on the part of the pharmacist to provide appropriate solutions for the same. The proposed model is also an effort towards the direction where the strategy based on machine learning will break down obstacles for patients with little awareness of their skin diseases. These patients will be able to upload a photograph of their diseased skin, which will be analysed by machine learning programme and it then will prescribe a suitable ointment. The model proposed is an extension of the currently available models in the field and will enhance them for practical utilization.

## II. REVIEW OF LITERATURE

Melanoma is one of the most prevalent skin disorders seen by dermatologists. The accuracy of a physician's visual diagnosis of melanoma is proportionate to his or her degree of experience and expertise in a particular specialty [5]. Adamson and Smith [6] examined the application of machine learning and artificial intelligence approaches in the area of dermatology with the aim of differentiating benign moles from malignant ones with the same degree of accuracy as board-certified dermatologists. The authors noted that machine learning, a kind of artificial intelligence may give dermatologists considerable aid in recognising and treating skin diseases, enhancing the quality of care delivered to patients. In addition, the authors cautioned that machine learning has the potential to exacerbate current healthcare inequities in dermatology if it is not designed from the start with inclusivity in mind.

Alarifi, Goyal, Davison, Dancey, Khan, and Yap [7] investigated skin classification algorithms that use traditional machine learning and cutting-edge Convolutional Neural Networks to classify three types of facial skin patches, viz. normal, spots, and wrinkles. These algorithms are used to classify a person's facial skin. The primary objective of the authors' study was to determine the standard deviation of the face skin quality score using the three categories, namely, normal, spots, and wrinkles. As part of their analysis, the researchers generated a derma dataset by gathering high-resolution images of diverse ethnic origins of faces of people. Then, they separated skin patches measuring 100 by 100 pixels into three unique groups. The authors spent some time fitting an appropriate model and tuning the parameters before concluding that among the many ML models, GoogleNet performed better than the Support Vector Machine technique. The accuracy of GoogleNet was 0.900, the F-measure was 0.852, and the Mathews correlation coefficient was 0.90. The correlation coefficient of the Support Vector Machine method was just 0.779%. According to the authors, the result shows that deep learning might be used to classify non-clinical skin scans, and that this application will be promising with a bigger dataset.

ALEnezi [8] tried to diagnose skin diseases using AI/ML. The author was of the view that computer vision played a crucial role in the identification of skin issues using a number of methodologies, with feature extraction playing a crucial role in the classification of skin illnesses. These therapies offer a significant lot of promise for treating skin ailments in Saudi Arabia, a nation with a high prevalence of skin diseases owing to the prevalence of deserts and high temperatures. The author presented an image processing-based method for the identification of skin disorders. The procedure involved taking a digital snapshot of a diseased region of skin and analysing the image to determine the exact condition. The authors suggested that the method receives a colour image as input, which is then scaled down and fed to a convolutional neural network that has been trained to extract features. Then, a Multiclass SVM classification is conducted on the data. The system's output contains the kind of disease, as well as its prevalence and severity. The author claims that the approach can properly diagnose three distinct skin illnesses in 100% of patients.

Ali, Li, Yang, and O'Shea [4] presented an automated method for recognising skin lesion boundary anomalies based on Convolutional Neural Networks and Gaussian Naive Bayes ensemble learning. This method involves the extraction of skin lesion from the image, detection of the skin lesion border, measurement of border irregularity, training of a Convolutional Neural Network, and a Gaussian Nave Bayes ensemble for the automatic detection of border irregularity, and an objective determination as to whether or not the skin lesion border is deemed to be irregular. According to the authors, the technique generated excellent results (accuracy: 93.6 %, sensitivity: 100 %, specificity: 92.5 %, and *F*-Score: 96.1 %).

Ayan and Ünver [3] conducted more research to identify skin lesions using deep learning. The authors feel that it is desirable to use data augmentation techniques when constructing a strong classifier with inadequate data. In this research, the same neural network model trained using improved skin lesion pictures and non-augmented skin lesion images for diagnosing malignant skin lesions was compared, and it was revealed that the network trained with augmented data produced greater results. The purpose of the research was to evaluate whether supplemented data may enhance the accuracy of neural network models.

Li and Shen [9] conducted more research to detect skin lesions using Deep Learning. The authors of this work provide two distinct deep learning approaches for addressing the three most major new concerns in skin lesion image processing. The necessary tasks include segmentation, the extraction of dermoscopic properties, and the classification of lesions. The authors enhanced the findings of the coarse classification by creating a lesion index calculation unit, which they did by calculating the distance heat map. The authors assess the proposed deep learning model using the ISIC 2017 dataset and a CNN for extraction of dermoscopic features. According to the authors, their frameworks exhibit respective accuracies of 0.753 for task 1, 0.848 for task 2, and 0.912 for task 3.

Hameed, Shabut, Ghosh, and Hossain [10] used machine learning algorithms to classify skin lesions into several categories and degrees. The authors provided a system that achieves a diagnosis accuracy of 96.47% and is assessed using 3,672 categorised images from a range of sources. The authors' multi-class and multi-level classification method improves the classification performance for recognising a broad range of skin lesions when compared to the prior multi-class and single-level classification strategy.

Dai, Spasić, Meyer, Chapman, and Andres [11] provided another illustration of how deep learning may be used to identify skin cancer. In this paper, the authors discussed the disadvantages of data-intensive approaches now used to diagnose skin cancer and proposed a solution to this problem. The authors pre-trained a convolutional neural network model using 10,015 images of skin cancer before deploying it on a mobile device where the inference process occurs, that is, when new images are presented and computations are executed locally (where test data remains), thereby reducing latency, conserving bandwidth, and enhancing privacy. The authors used 10,015 skin cancer photos.

Gavrilov, Melerzanov, Shchelkunov, and Zakirov [5] worked on the detection of melanoma. The authors offer a strategy for the early diagnosis of melanoma based on artificial deep Convolutional Neural Networks. According to the researchers, analysis of dermatological photos allows their technology to distinguish between benign and malignant types of skin cancer with an accuracy of at least 91%.

Utilizing computer vision and machine learning effectively, Kumar, Kumar, and Saboo [1] provide a two-stage technique for detecting dermatological diseases. This approach is available in their paper. Following the conclusion of the first step, which consists of the diverse pre-processing of the data, the characteristics will be extracted. In the second step of the procedure, machine learning algorithms are utilised to discover abnormalities based on the skin exam's histological characteristics.

Liaqat, Dashtipour, Arshad, and Ramzan [12] concentrated on the use of non-invasive wearable sensors for gathering skin conductance data and the implementation of various machine learning algorithms based on feature engineering for the prediction of the human body's hydration level in different body postures. These techniques were used to assess human body's hydration level in various situations. The researchers examined a range of machine learning techniques and determined that random forest had the greatest accuracy rate (91.3%).

Mhaske and Phalke [13] used Machine Learning techniques to recognise and classify melanomas. Support Vector Machines and neural networks are among these approaches used when skin cancer is at its early stages. Mishra and Celebi [14] presented an overview of clinical feature segmentation and described the classification phase, which is the stage when Machine Learning approaches may be used to segment data features to predict the presence of melanoma. Murugan, Nair, Preethi, and Kumar [15] examined a variety of Machine Learning techniques for the goal of detecting skin cancer instances.

Mobiny, Singh, and Nguyen [16] studied how Bayesian Deep Learning might enhance the effectiveness of the machine-physician cooperation in the categorization of skin lesions. The authors used the HAM10000 dataset, which is accessible to the general public and contains samples from the seven most prevalent skin lesion types. Experiments indicate that Bayesian deep networks have the ability to boost diagnostic performance of the conventional DenseNet-169 model from 81.35% to 83.59% without the need for extra parameters or intensive processing. According to the results of this study, a workflow that mixes people and robots may achieve 90% classification accuracy while referring just 35% of cases to medical specialists.

Ozkan and Koklu [17] pre-classified skin lesions into three groups: normal, abnormal, and melanoma using Machine Learning techniques. In addition, they employed these methodologies to construct a decision support system that should aid clinicians in taking decisions. This paper investigates the identification of skin lesions based on dermoscopic photographs PH2 datasets using four distinct machine learning algorithms, including ANN, SVM, KNN, and Decision Tree. From the PH2 database, the datasets were collected. According to the authors, the ANN model has an accuracy of 92.05%, the SVM model has an accuracy of 89.5%, the KNN model has an accuracy of 82%, and the DT model has an accuracy of 90%. According to the study's authors, the data shows that the system built as part of this analysis is a medical decision support system that might be useful to dermatologists in the identification of skin lesions.

Rathod, Waghmode, Sodha, and Bhavathankar [18] created an automated image based approach for the identification of skin disorders. This approach employs categorization by Machine Learning. According to the authors, the system may employ computational techniques to assess, analyse, and assign image data based on a broad range of image properties. The photos of the skin are processed to enhance image quality and are filtered to remove noise. A diagnostic report is created as an output after the extraction of features using a Convolutional Neural Network (CNN), the classification of pictures using the softmax classifier approach, and the generation of a diagnosis report. This happens when a diagnostic report has been generated. The researchers assert that this procedure is more exact and yields results in less time than the conventional method; hence, using this application is a trustworthy and effective method for identifying dermatological diseases. In addition, the authors believe that this technology might be used as an effective real-time teaching aid for medical students studying dermatology. Udrea, Mitra, Costea, Noels, Wakkee, Siegel, de Carvalho, and Nijsten [19] created a smartphone application capable of detecting skin lesions by analysing a picture of the afflicted region.

Vidya and Karki [20] and Vijaylakshmi [21] examined the diagnosis of skin cancer using image processing and machine learning. Both of these studies demonstrate a high degree of accuracy in identifying skin cancer, and they both propose using CNN and other machine learning models for this purpose.

## III. RESEARCH GAP

All these studies have more or less been directed to the area of developing machine learning based models for detecting skin related problems. However, any work has yet to been done to propose an integrated system which will not only detect skin-related problems, but will also suggest suitable pre-programmed remedy for the same. The current work is an effort towards that direction and it not only uses a CNN-based model to detect skin-related issues but also propose suitable remedy for the detected skin problem.

## IV. METHODS AND METHODOLOGY

The framework is primarily based on the Convolutional Neural Networks (CNNs) which is a kind of Artificial Neural Network model utilised extensively in Deep Learning to analyse visual input. Multi-layer Perceptron Networks (MLPN) are the regularised form of Convolutional Neural Networks. In the case of a convolutional network, a filter is employed to extract a subset of the dimension's important properties, following which further processing is performed. Fig. 1 is an example of a Convolutional Neural Network.

CNNs have several potential applications, including as image and video recognition, recommender systems, image classification, image segmentation, medical image analysis, natural image processing, and financial time series analysis. Regarding multilayer perceptrons, every neuron in one layer is linked to every neuron in the layer that follows it. These networks are susceptible to data overfitting because of their "completeness" or "full connectedness”. The penalization of training parameters

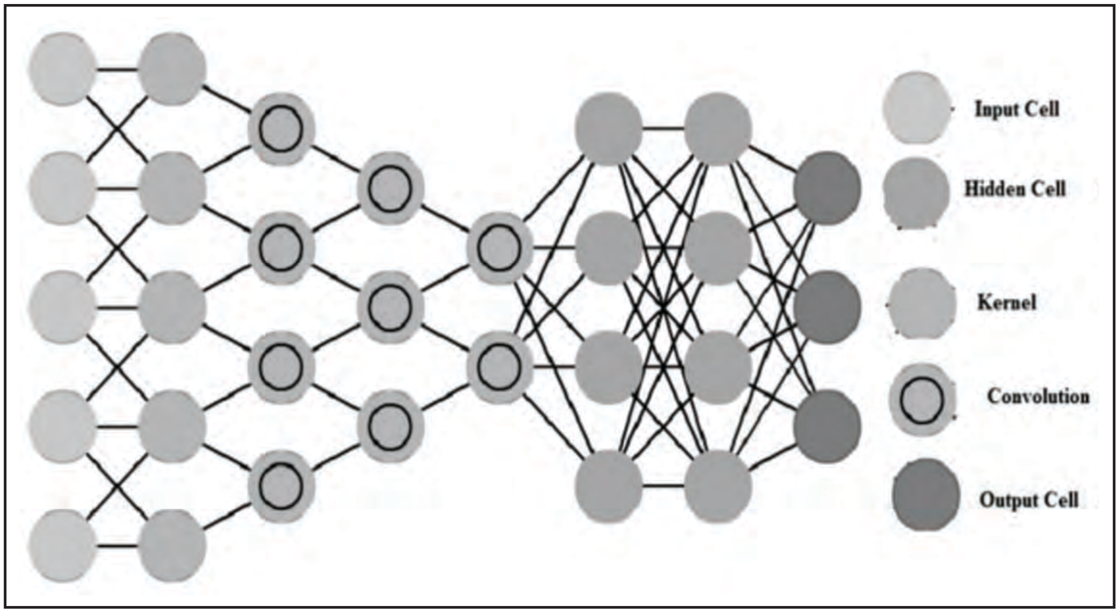


**Fig. 1. Convolutional Neural Networks**

is a common method for regularising data or preventing overfitting.

Regularized multilayer perceptrons constitute CNNs. Multilayer perceptrons are often used to describe networks in which every neuron in one layer is linked to every neuron in the layer that follows it. These networks are susceptible to data overfitting because of their "completeness" or "full connectedness." Regularization, also known as the avoidance of overfitting, is often accomplished by penalizing training parameters (such as weight decay) or by limiting connectivity. Both of these methods are used (skipped connections, dropout, etc.) CNNs use an approach unique from regularisation; they utilise the data's inherent hierarchical structure to construct more complex patterns by layering simpler patterns imprinted in its filters. Consequently, CNNs are at the absolute bottom of the spectrum in terms of connectivity and complexity.

Maxpool Layer: Max pooling is a pooling approach that picks the greatest element from the area of the feature map covered by the filter. This piece has been selected from the whole feature map. Therefore, the result of the max-pooling layer would be a feature map including the most prominent features from the previous feature map.

Layer flattening is the process of transforming data into a one-dimensional array so that it may be put into the following layer. By flattening the output of the convolutional layers, a single, extensive feature vector is generated. A layer is considered to be fully connected to the overall classification model when it is coupled to that model.

Every neuron in a thick layer gets information from all of the neurons in the layer underneath it. Therefore, the neurons in this layer are highly linked. In other words, every neuron in the dense layer is related to the neurons in the layer above.

Here, an effort has been made to use two models – one custom-developed CNN model with 3 Convolutional Layers and 3 Max-pooling layers, 1 flatten layer, and 2 dense layers, and the other standard Inception V3 model developed by Google.

## V. DATASET USED

Around 200 labelled images of different image related issues - Acne, Ageing, and Redness have been collected and have been used for training the system. The labelled images were collected from the internet. Corresponding specific remedies also have been mapped in the system. Fig. 2 shows sample skin images.

## VI. SUGGESTED FRAMEWORK

The framework has been proposed (Fig. 3) based on Deep Learning techniques application for identifying the skin issue and suggesting the most appropriate remedy for the same.

The suggested framework is tested with the dataset.

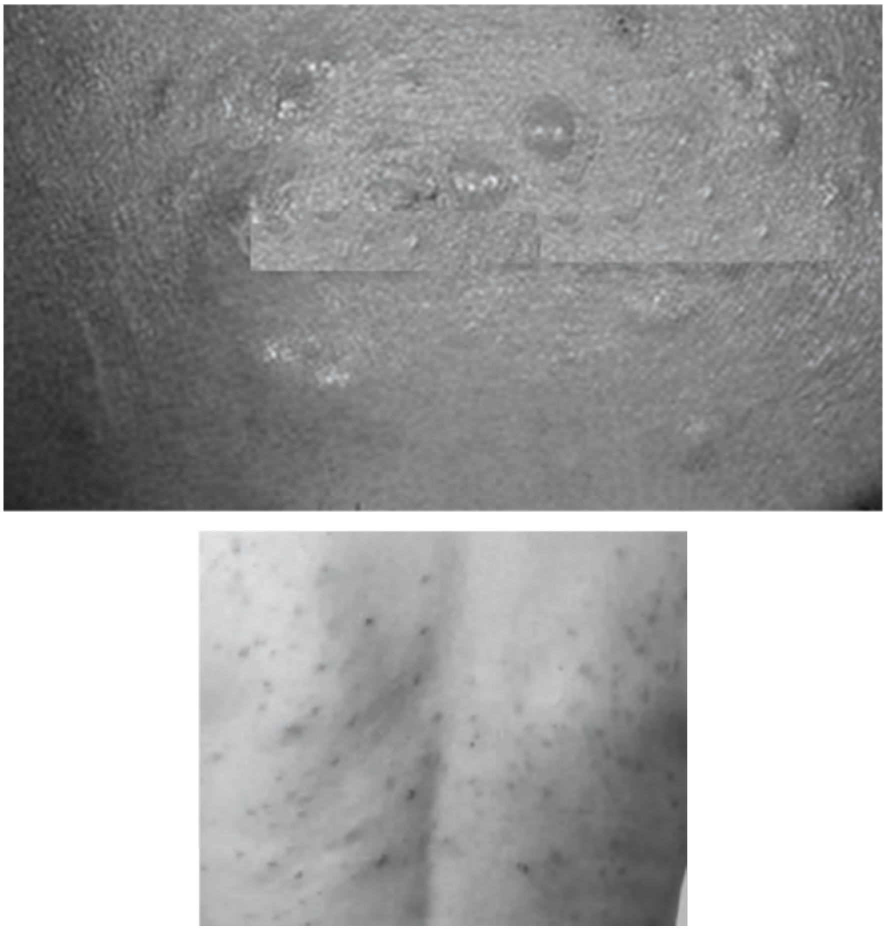

Fig. 2. Sample Skin Images

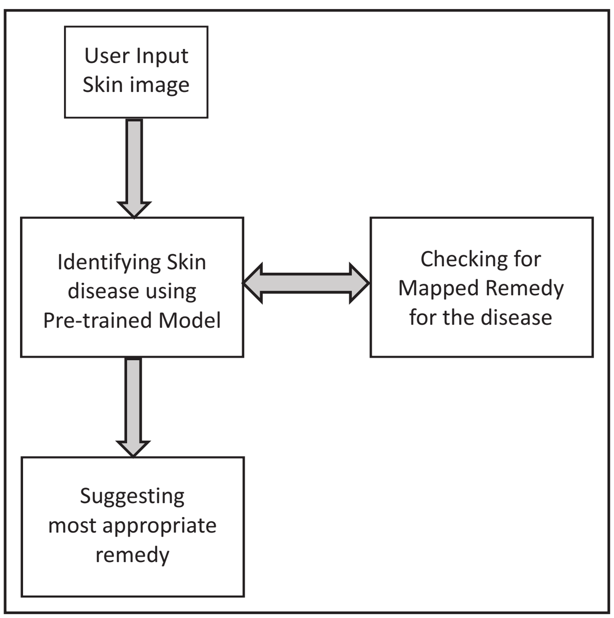


Fig. 3. Proposed Framework

For the study 200 images were considered with 180 images as the training set and 20 images as the test set.

## VII. RESULTS AND DISCUSSION

The model details have been presented in Table I.

TABLE I.
MODEL SPECIFICATIONS

| CNN Model | Inception V3 Model |
|---|---|
| Convolutional Layers = 3 | Pretrained Count of Parameters = 5432713 |
| Max-pooling Layers = 3 | Dense Layer = 3 |
| Flatten Layers = 1 | Parameters used in Dense Layer = 3006 |
| Dense Layers = 2 | |

**TABLE II.**
**MODEL FIT RESULTS**

| Model | CNN model | Google Inception V3 Model |
|---|---|---|
| Test Data Accuracy | 85% | 98% |
| Area Under Curve (AUC) | 83% | 94% |
| Loss Value | 9.39 | 0.2 |

0

The CNN model used was a custom model whereas the Inception model used was a pre-trained model developed by Google and available in the Python Keras library.

As per the classification done, the framework based on Python-Flask suggests the best remedy for the skin problem. Fig. 4 shows application execution. Fig. 5 shows sample output of remedial products recommendation.

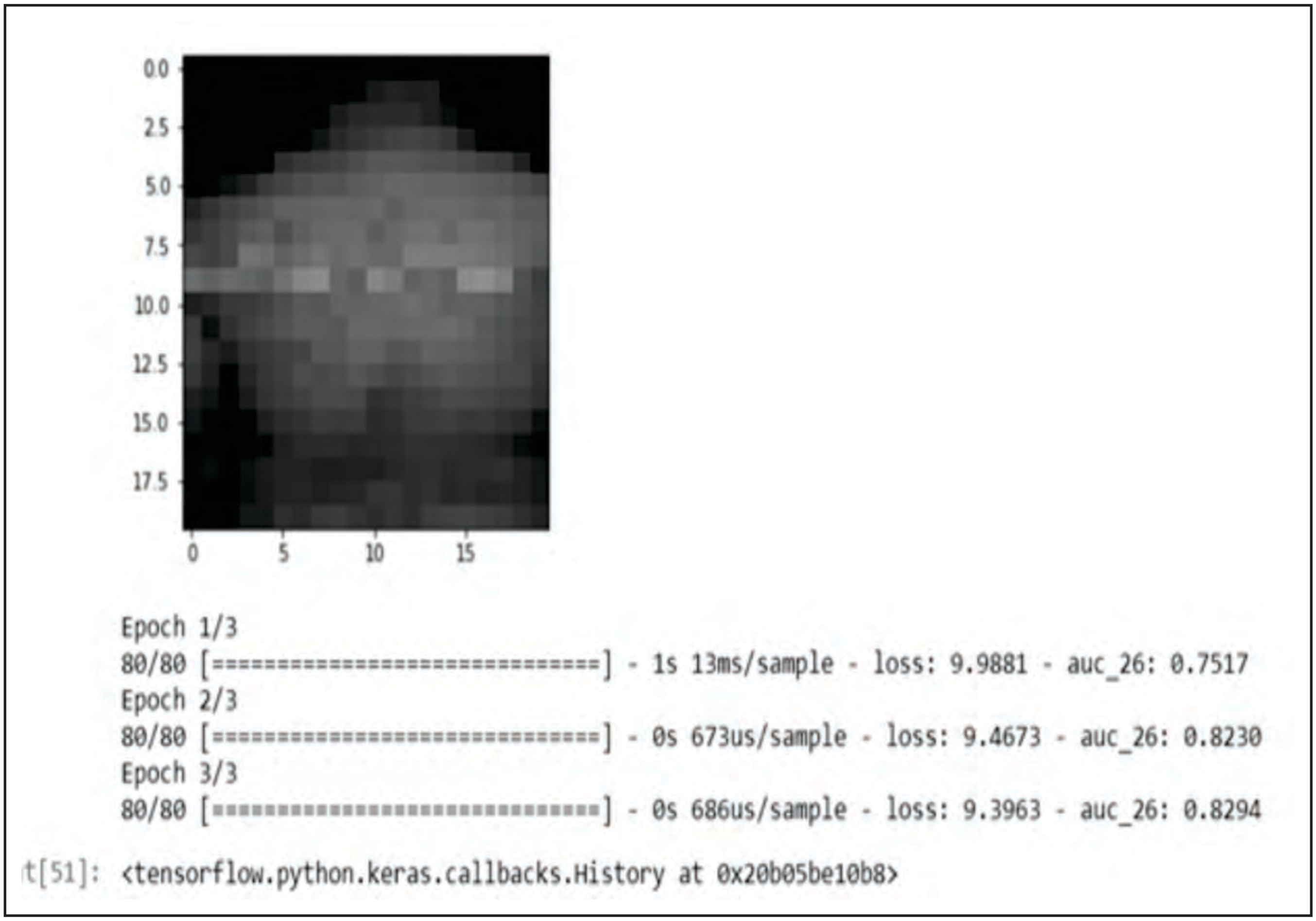


**Fig. 4. Application Execution**

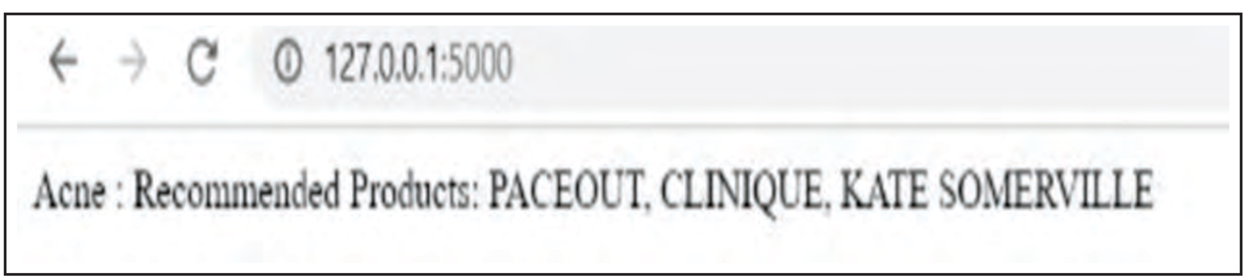


**Fig. 5. Remedial Products Recommendation (Sample Output)**

## VIII. CONCLUSION

The used models CNN and Inception V3 gave better accuracy for detecting skin problems than the currently available models found in literature. This work has also tried to develop a framework where the deep learning technique can be used to provide instant solution to patients' query online regarding skin issues and suggest proper remedy for the same. Skin related issues are quite common among individuals, however, inherent social stigma specially in the third world countries attached to skin related issues restricts people to seek appropriate help from dermatologists unless it goes out of proportion. Any application developed on the basis of the mentioned framework will help patients ask for proper support and treatment and will greatly decrease their skin related issues. CNN and Inception V3 models work extremely well in detecting skin related issues as seen from the study. This work will greatly help in facilitating further works in the direction of easing individual patient's quest for getting appropriate treatment for skin related issues.

## AUTHOR'S CONTRIBUTION

Dr. Subhabaha Pal is the sole author of this paper and performed the whole work described in the paper independently. He had prepared the training and testing dataset, ran different models and analyzed the output.

## CONFLICT OF INTEREST

The author certifies that he has no affiliations with or involvement in any organization or entity with financial implications in the subject matter presented in the paper.

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