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ENHANCED SKIN DISEASE DETECTION USING THE THREE PROPOSED DISTINCT CNN MODELS

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ABSTRACT

Dermatology is the name for the area of medicine that deals with skin. Due to the intricacy, it is considered to be one of the clinical branch's hardest areas to diagnose. Skin cancer and dermatological illnesses are very challenging to visually diagnose in the early to middle stages of the disease. Additionally, the time it takes to diagnose a skin condition might differ from practitioner to practitioner and also be influenced by the practitioner's level of experience. If an illness, such as melanoma, is not treated in a timely manner, it may have very serious consequences. Therefore, a method that can identify skin illnesses without any of these limitations is required. Self-assessment may also prove to be the best option in areas where proper resources are few, such as in rural and congested areas. We suggest a machine learning-based, automated method for processing images to identify skin diseases. The skin disease image is initially subjected to several pre-processing methods used in image processing. Machine learning methods are used to identify disorders in second stage. Unwanted noise is removed from skin photos. Convolutional neural networks (CNNs) will be a key component of the system's overall synthesis. We are proposing three models on which we did training and further testing is done by test data set. Three distinct CNN models were designed and trained using a diverse dataset of dermatological images. The models were evaluated using a rigorous cross-validation technique to assess their performance with regard to accuracy. The findings shows that Model 1 achieved an accuracy of 80.5%, Model 2 reached 85%, and Model 3 exhibited an accuracy of 65% in the categorization of skin diseases. Our study highlights the potential of CNN-based models in automating the detection of skin diseases, with Model 2 demonstrating the highest accuracy among the three models. These results highlight deep learning's potential in the dermatological discipline and suggest that further research and even more accuracy can result from model design advancements and reliable skin disease detection systems. This suggested method will concentrate on obtaining more precise findings, and it may be applied globally without a lot of expensive equipment or resource needs.

Keywords: Artificial Intelligence, Machine Learning, Convolution Neural Network, Skin Disease.

I. INTRODUCTION

Diseases are regarded as a specific kind of medical sickness characterized by a given set of symptoms. The disease can be categorized based on the extent to which the body is affected, for example. Diseases can locally impact specific bodily parts, diffuse to other body parts, or affect the entire body in the case of systemic disorders. Problems affecting a person's skin are called skin disorders. It seriously affects people's health. Since this is so common, finding efficient treatments is now essential. Skin conditions can have a major negative influence on a patient's quality of life.[15] Skin disease might cause people to suffer significant loss, thus early detection is quite important. An automated diagnostic tool that would support in disease diagnosis at a faster rate is required in today's environment. In the modern world, an automatic diagnostic system is required to identify the cause of the illness more quickly and, due to that, cut down on the manual efforts and time needed to identify the illness. With a photograph of the affected area as an input, our suggested solution uses a convolution neural network, that aids in identifying skin conditions. The algorithm then analyzes and groups the images into several categories.

We use a broad dataset of five distinct kinds of skin disorders in our study, i.e., Basal cell, Eczema, Keratosis, Melanoma and Psoriasis. We preprocess and augment the data to enhance the model's ability to generalize across different skin types and disease manifestations. Our proposed ML framework comprises convolutional neural networks (CNNs), which have performed remarkably well in image classification tasks. We fine-tune pre-trained CNN models and adapt them to the specific requirements of identification of skin diseases. We create a user-friendly web-based interface for uploading skin photos and getting quick diagnostic findings to make it easier for real-world application. Both healthcare experts and those who are worried about the condition of their skin can use this interface.. In conclusion, this paper highlights the potential of machine learning as a useful instrument in the dermatology area. By combining advanced ML techniques with a user-friendly interface, we aim to revolutionize the way skin diseases are diagnosed and managed, paving the way for more efficient and accessible healthcare service.

II. LITERATURE SURVEY

In the field of artificial intelligence, identifying and categorizing skin diseases has long been an issue. The skin disease picture database was used to test several feature engineering techniques before deep learning, and different classical machine learning algorithms were used to detect skin diseases and classify their families. Nonetheless, the literature review reveals that deep learning techniques have been used for both skin disease classification and identification, given the current explosion of deep learning approaches in performance enhancement in a variety of medical imaging applications. Authors Aswin.R.B, J. Abdul Jaleel and Sibi Salim [1] proposed an artificial neural network-based classification methodology for skin cancer detection that leverages artificial intelligence and image processing tools for early diagnosis. Certain distinguishing characteristics between benign and malignant melanoma were taken out in order to simplify the classification process. The feature extraction method that is employed is 2D Wavelet transform. The Artificial Neural Network Classifier receives these features as input. The provided data set is categorized as either cancerous or non cancerous. Md. Humayan Ahmed, Romana Rahman Ema and Tajul Islam [2] proposes detection of different types of dermatological diseases using a novel hybrid intelligent ACO-GA algorithm that combines the ACO Algorithm, GA, and tabu list. This algorithm is used for the segmentation of different types of skin lesions in dermatological images, and it uses Transductive Support Vector Machine (TSVM) to identify dermatological diseases. Using a hybrid ACO-GA method, the system's implementation separates the colored skin picture and uses a TSVM classifier to identify skin cancer and dermatological skin diseases. Then, the hybrid ACO-GA algorithm aids TSVM in accurately examining skin conditions. Cueva, W. F., Munoz, F., Vasquez, G., & Delgado., G. [3] suggests a model for identifying skin cancer. Melanoma, which can be identified by its Asymmetry, Border, Color, and Diameter (ABCD) using image processing. Classifying the various types of moles are performed using neural networks. The system's great efficiency is attributed to its ability to do analysis and image processing in brief bursts of time.

Jeffrey Glaister, Alexander Wong and David A. Clausi [4] proposes a segmentation approach for the diagnosis of melanoma illness is presented in this paper. By contrasting the outcomes of melanoma classification and lesion segmentation with those of other cutting-edge algorithms, the suggested segmentation framework is put to the test. To find skin lesions in photos, a segmentation technique is based on texture distinctiveness (TD). Chaahat Gupta, Naveen Kumar Gondhi and Parveen Kumar Lehana [5] proposes a Mahalanobis distance metric to analyze and classify skin diseases from their visual images using the Gaussian mixture model (GMM).The modeling of contrast, correlation, energy, and homogeneity using GMMs revealed that the peak structures of various dermatological disorders are distinct, making it possible to forecast them with ease solely from colored photographs.Soumya Saurav, Nikhil Garg and Yasha Hasija [6] presents an automated approach that, in contrast to the typical medical personal based detection, uses lesion images to recognize dermatological diseases. The three stages of the model's design are data gathering and augmentation, model design, and prediction. Several artificial intelligence (AI) methods, such as Convolutional Neural Network and Support Vector Machine, are combined with image processing technologies to create a more accurate structure.

Hegde, P. R., Shenoy, M. M., & Shekar, B. H. [7] suggests comparing the classifiers of machine learning algorithms. Using a digital camera, they gathered pictures of plaque psoriasis, lichen planus, and chronic eczema. They then extracted the texture features known as Gray Level Co-occurrence Matrix (GLCM) and the RGB color features. The performances of the classifiers were then compared using four ML methods and various feature combinations. Gnanasigamony Wiselin Jiji, Peter Savariraj Johnson Durai Raj [8] suggests an architecture that uses extracted image elements including shape, texture, and color to retrieve digital photos

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and the name of the corresponding disease category from an image data repository. Regression trees, classifiers, and feature vectors are used by this approach to extract contents from images.

V.B.Kumar, S.S.Kumar and V.Saboo [9] suggests a method for accurately identifying skin diseases by using machine learning and computer vision on clinically assessed histopathological features. While machine learning is used to identify images, computer vision encompasses tasks like feature extraction and pre-processing. A.Rajesh, [10] described work on early detection of two types of skin cancer: non-melanoma and melanoma that poses a concern, using highlight extraction and division. For improved outcomes, apply the thresholding strategy. The ABCD score is examined, including the Asymmetry, Border, Colors, and Dermoscopic Structures criteria. J.Rathod, V.Waghmode, A.Sodha and Dr.P. Bhavathankar [11] presents an automated machine learning-based image-based method for the detection of skin diseases. Convolutional neural networks and softmax classifiers are used in feature extraction to identify the type of diagnosis report. After initial instruction, accuracy was 70%. Mrs. S.Kalaiarasi, H. Kumar and S. Patra [12] proposes an application that uses machine learning and image processing to diagnose skin diseases. The algorithm was able to diagnose the ailment with fewer error even though the machine learning data-set was limited. Because it is lightweight, the application can be utilized on machines with modest system requirements. J. Yang, X. Sun, J. Liang and P. L. Rosin [13] suggests a computer-measureable approach that is based on the criteria used by clinicians to make diagnoses. Based on these qualities, they created a skin disease diagnosis method and created six medical representations that took into account various criteria for identifying skin lesions. R. Yasir, Md. A. Rahman and N. Ahmed [14] proposed a method for the detection of different types of dermatological skin illnesses using computer vision techniques. Various kinds of image algorithms are employed for training and testing purposes in feature extraction and feed forward artificial neural networks. The system operates by first extracting important information from color skin photos through pre-processing, and then it diagnoses the disorders. A.A.L.C. Amarathunga, E.P.W.C. Ellawala, G.N. Abeysekara, C. R. J. Amalraj [15] describes the development of a skin disease diagnosis system that enables users to quickly diagnose skin problems in people and offer recommendations or medical treatments. It will be utilized to identify skin conditions and suggest a course of treatment.

Sudha J, Aramudhan M and Kannan S [16] introduces The Response Surface Methodology (RSM), which uses independent and dependent variables to predict psoriasis patients by establishing a link between input properties of skin diseases. The RSM model's performance demonstrates the established empirical relationship and exhibits the highest degree of test-retest conformance. To analyze the results mathematically, the Analysis of Variance (ANOVA) is used. Srujan S A, Chirag M Shetty , Mohammed Adil ,Sarang P K , Roopitha C H [17] proposes a Convolutional Neural Network method to detect seven types of skin cancer: Melanocytic Nevi, Melanoma, Actinic keratoses, Vascular lesions, Basal cell carcinoma, Melanocytic Nevi, and Dermatofibroma. Keshetti Sreekala, N. Rajkumar, R. Sugumar, K. V. Daya Sagar, R. Shobarani, K. Parthiban Krishnamoorthy, A. K. Saini, H. Palivela, and A. Yeshitla [18] studies a range of tactics and approaches to recognize and halt illnesses early. They all produce good results for recognizing and classifying diseases; nonetheless, the research states that proper disease categorization is still missing. Based on the foregoing considerations, it can be said that the majority of research to date has been done to identify specific groups of skin diseases. Most of the pieces are centered around a specific illness. Merely a handful of the completed studies are insufficient for categorizing several classes. The majority of them use tiny datasets for their operations. In our research, in contrast to limiting the type of skin illness to one, we have taken into account a variety of disease types in our research by using a wider number of datasets. Preprocessing of the data has also been our main focus. Users would find it incredibly easy to use an application that lets them take a snapshot of their skin condition and get instantaneous predictions right away.

III. METHODOLOGY

Convolutional Neural Networks (CNN) have emerged as an effective instrument in the computer vision field and image analysis, offering a promising avenue for automating the evaluation of a skin condition. In this section, we will outline the methodology employed for identification of skin diseases using CNNs, highlighting the key steps and principles that underpin this innovative approach. Through this methodology, we leverage the capabilities of CNNs to enhance the precision and efficiency of skin disease diagnosis, ultimately improving patient outcomes.

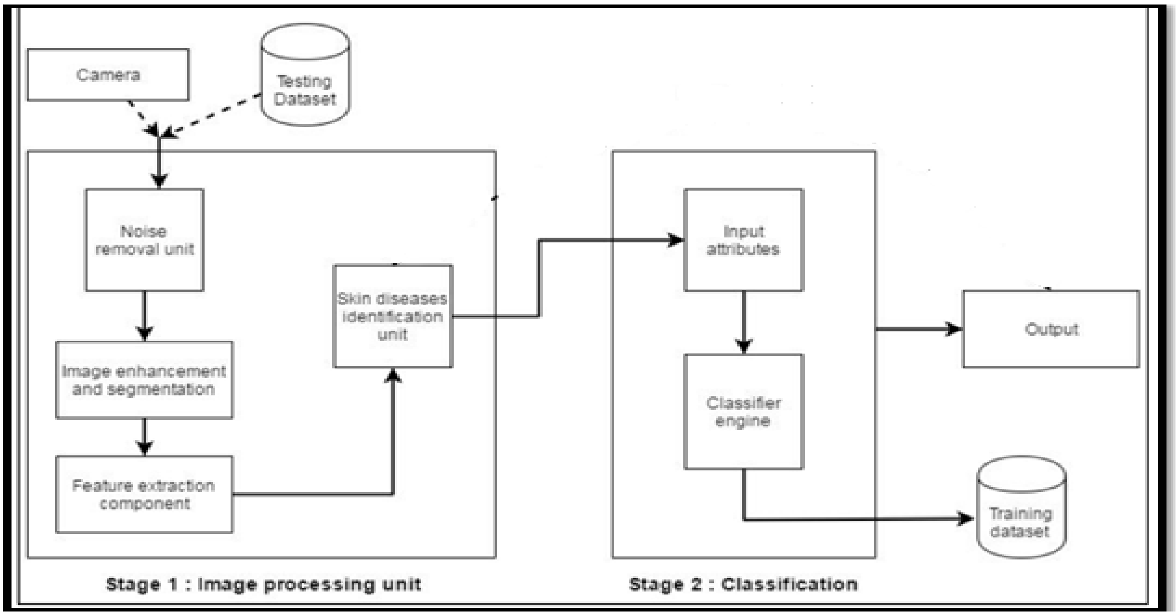

Figure 1: Block diagram[11]

1. Data preprocessing

Different steps in data preprocessing are described as below :

1.1 Data collection

From publicly accessible dermatology sources, we gathered a varied dataset of photos depicting skin diseases. The collection includes pictures of five distinct types of skin conditions, including basal cell, eczema, keratosis, melanoma and psoriasis.

1.2 Data Storage

Component for storing data to preserve training and testing data images: A training dataset is necessary for using supervised learning, as this instance does. The photos that were taken during image acquisition make up the testing dataset.[16]

1.3 Data processing

Prior to training our CNN model, we performed the following preprocessing steps:

- In order to normalize the image and prevent analytical confusion, noise such as skin and hair pigments are removed. It is also vital to determine the needed image size because the input image may not be of the standard size that the algorithm requires.
- Image Resizing: All images were resized to a uniform resolution of 150X150 to ensure consistency.
- Data Split: Three subsets of the dataset were created: 80% for training, 10% for validation, and 10% for testing.

2. Skin disease identification unit, Feature extraction and Classification

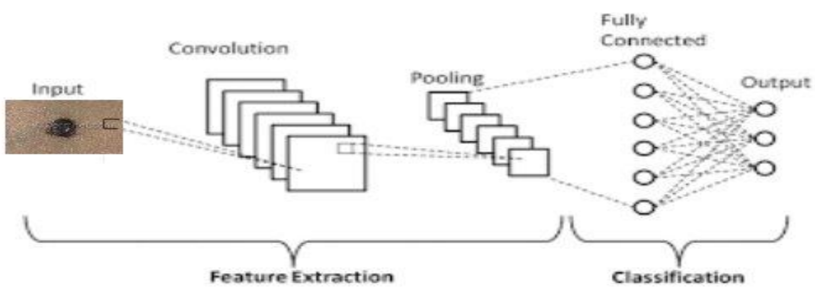

Figure 2: Feature extraction and classification[19]

This research presented a model that CNN received training on identifying skin conditions. The proposed algorithm's fundamental architecture is as follows :

Input layer : Images of skin conditions will be used as input in our study. The settings specify the size of image.

Convolutional Layers: CNNs are composed of convolutional layers. Using a collection of teachable filters known as kernels, these layers change the incoming image. Each filter calculates the dot product as it passes over the input image between itself and the local region. By employing this technique, feature maps are produced that highlight the image's many patterns, such as edges, textures, and more complex structures. A 3x3-inch filter will be used with three layers.

Subsequent feature map values are calculated according to the following formula, where the input image is denoted by f and our kernel by h. The indexes of rows and columns of the result matrix are marked with m and n respectively.[20]

$$G[m,n] = (f * h)[m,n] = \sum_j \sum_k h[j,k]f[m-j, n-k] \quad (1)$$

Activation Functions: The feature maps are activated after each convolution step, typically using a ReLU, or Rectified Linear Unit. The network gains non-linearity as a result, and it may learn complex representations. Deep convolutional networks based on ReLU is far faster to train than sigmoid and tanh-based models. For each convolutional layer, we'll use four ReLU layers. The formula for the ReLU activation function is as follows: [21]

$$f(x) = \max(0,x) \quad (2)$$

where, f(x) represents the output of the ReLU activation for a given input x.

x is the input to the ReLU function.

Pooling Layers: Pooling layers, also known as Max Pooling or Average Pooling, are used to reduce the spatial dimensions of feature maps, while preserving their most important information. By lowering the quantity of parameters in the network, pooling makes it more adaptable to small translations.

Feature maps undergo numerous convolutional and pooling layers before being flattened into a 1D vector. This vector is then passed into layers that are entirely connected.

Max pooling was employed in the suggested architecture to determine the maximum value in each patch for each feature map. With a stride of 2, the maximum pooling will be set to 2x2. This is formulated as : [22]

$$Y[i,j] = \max_{m,n}(X[i \cdot s+m, j \cdot s+n]) \quad (3)$$

where, Y[i,j] is the output value at position (i,j) in the pooled feature map.

X is the input feature map.

s is the stride, which is the step size for moving the pooling window.

m and n are the indices within the pooling region.

Fully Connected Layers: Every neuron in a traditional neural network's fully connected layer is connected to every neuron in the layer above it. Fully connected layers produce the combined retrieved features and final predictions based on these features. In this model, there is only one inner-product layer.

Training Procedure : Ten epochs of the training dataset were used to train our model. We used early stopping based on the validation loss to prevent overfitting.

Classification : The final layer of the network that provides the actual probability of each label is the Softmax classifier.[11]

IV. MODELING AND ANALYSIS

Three alternative convolutional neural network-based models for forecasting skin conditions from the skin disease dataset have been developed in this research. The complete algorithm development procedure is carried out in Python. Librares such as numpy, pandas, pillow, flask, FLASK_CORS, sklearn, keras, tensorflow are used. The dataset was taken from dermnet.com.

Model 1:

A 100 x 100 RGB-enhanced image of the specified size is supplied into the input layer. The output layer is the flattened layer from the output, and here the data will be turned into a 1-dimensional array before being provided to a fully connected layer of 512 neurons. A series of convolution, batch normalization , activation, and dropout is conducted 3 times one after other, and later max pooling is applied. The flatten layer formed is of size 1600 which then gives a dense output of 512. The final dense layer of the network, known as the softmax classifier, generates each label's true probability. The five skin diseases will be output in categories as a result.

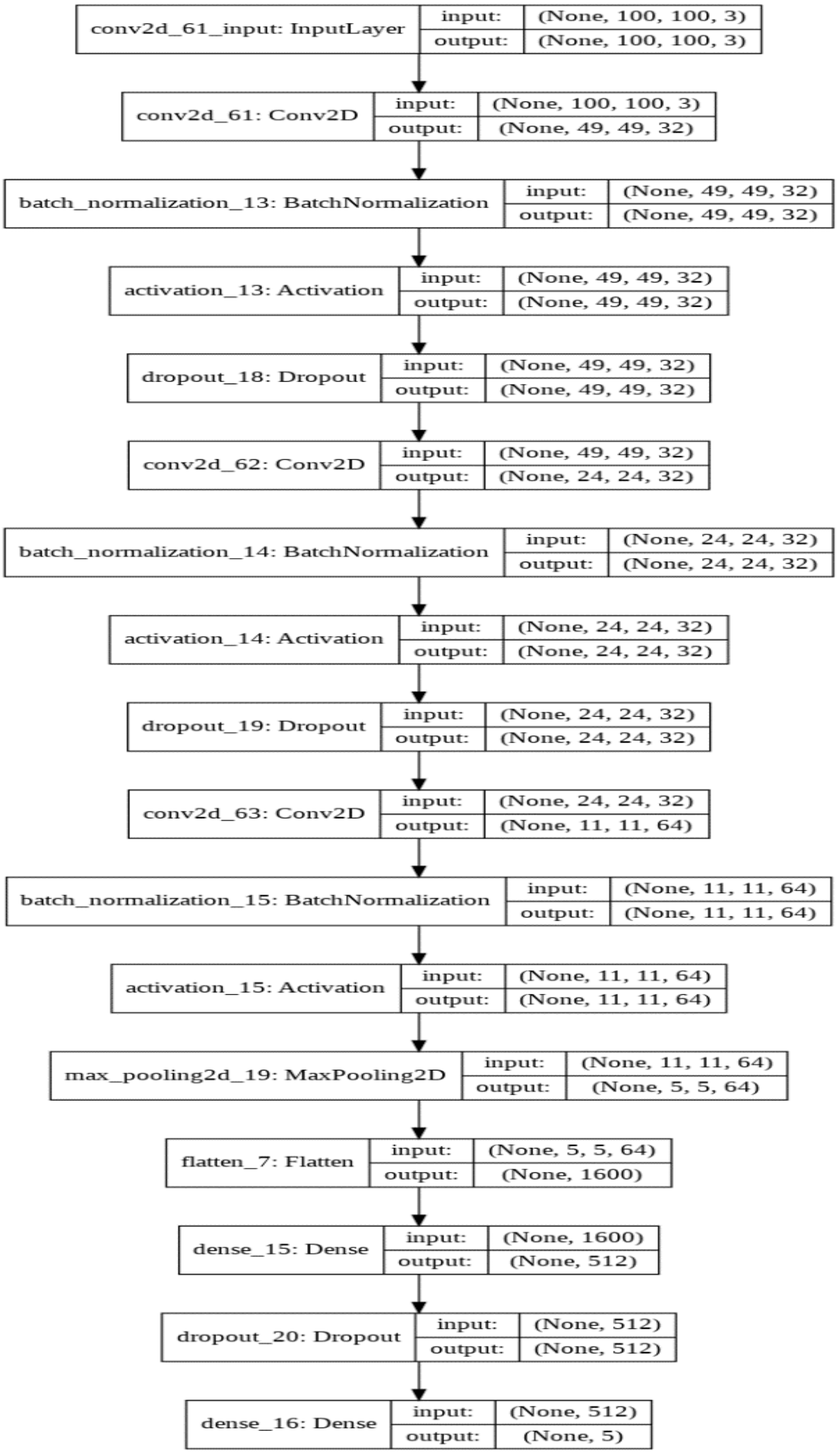

Figure 3: Model 1

Model 2:

A 100 x 100 RGB-enhanced image of the specified size is supplied into the input layer. The input image is filtered by the first convolution layer. The output layer is the flattened layer from the output, and here the data will be turned into a 1-dimensional array before being provided to a fully connected layer of 512 neurons. A series of convolution, batch normalization , activation, and dropout is conducted 5 times one after other in this model, with a slight exception in 3rd round where instead of dropout max pooling is applied. The flatten layer

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formed is of size 192 which then gives a dense output of 512. The final dense layer of the network, known as the softmax classifier, generates each label's true probability. The five skin diseases will be output in categories as a result.

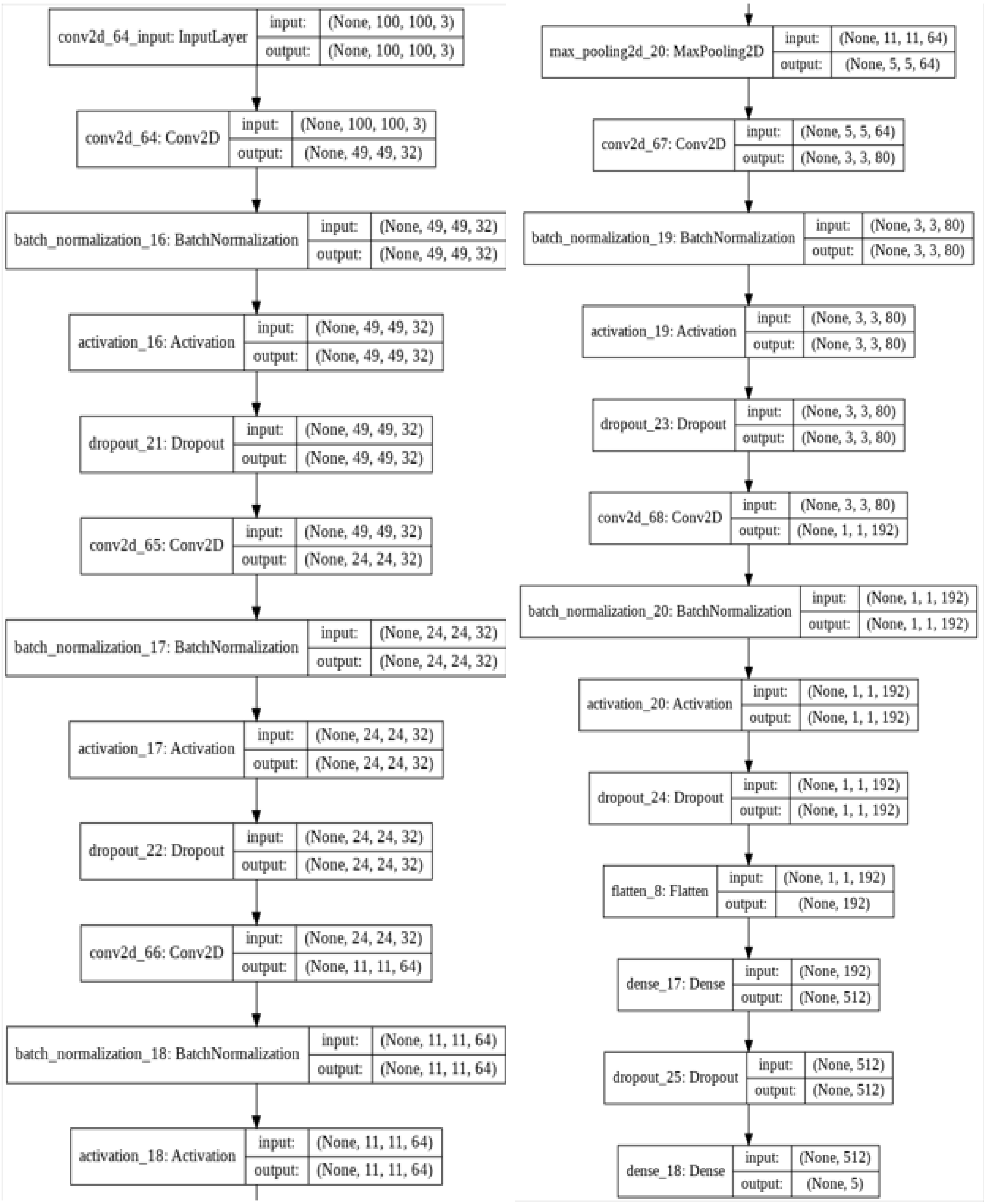

Figure 4: Model 2

Model 3:

A 100 x 100 RGB-enhanced image of the specified size is supplied into the input layer. The input image is filtered by the first convolution layer. The output layer is the flattened layer from the output, and here the data will be turned into a 1-dimensional array before being provided to a fully connected layer of 4096 neurons. A

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series of convolution and max pooling is applied 5 times. The flatten layer formed is of size 4608 which then gives a dense output of 4096. The final dense layer of the network, known as the softmax classifier, generates each label's true probability. The five skin diseases will be output in categories as a result.

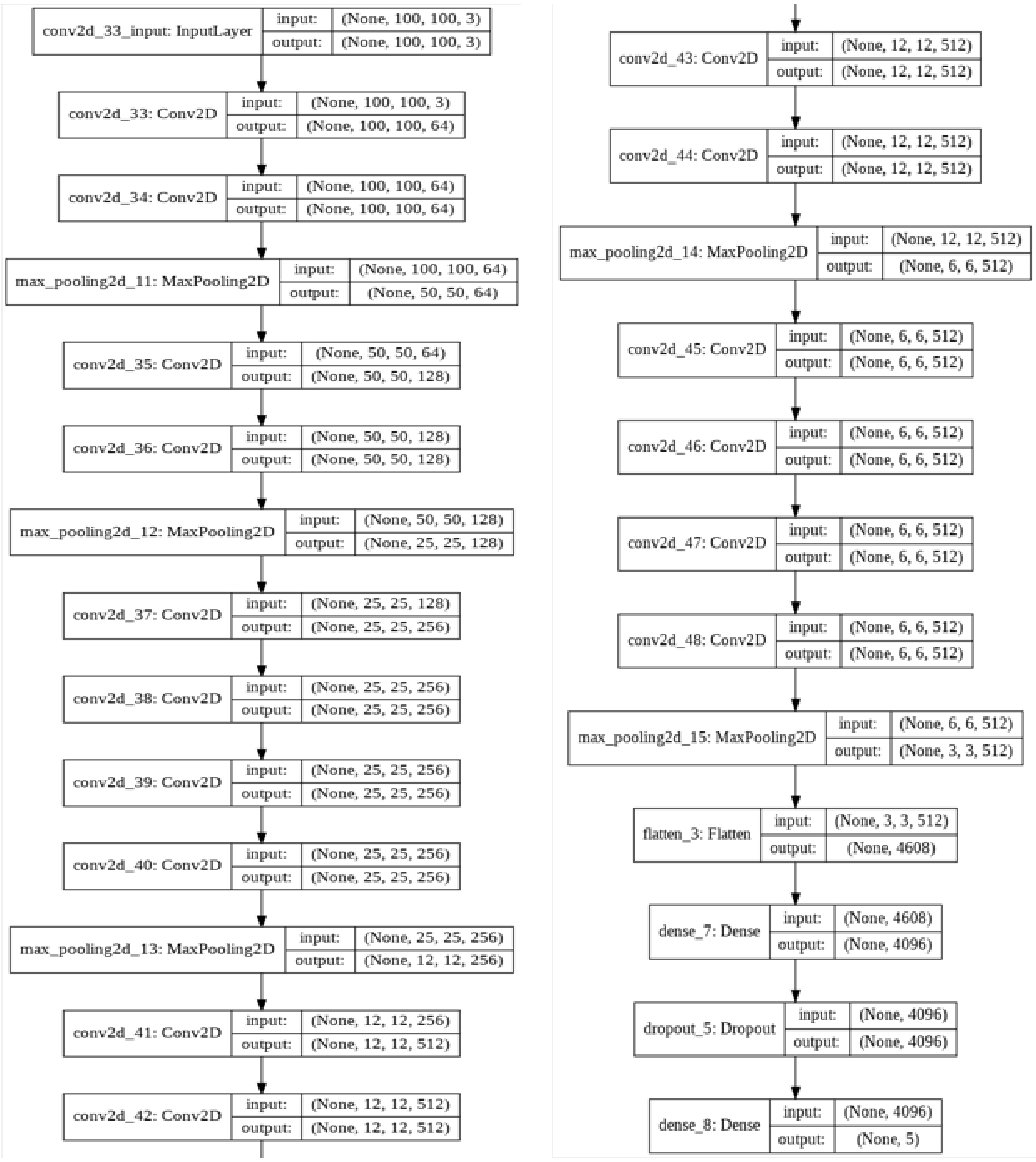

Figure 5: Model 3

V. RESULTS AND DISCUSSION

For the proposed 3 models, we have Model accuracy and loss graphs.

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Model 1 :

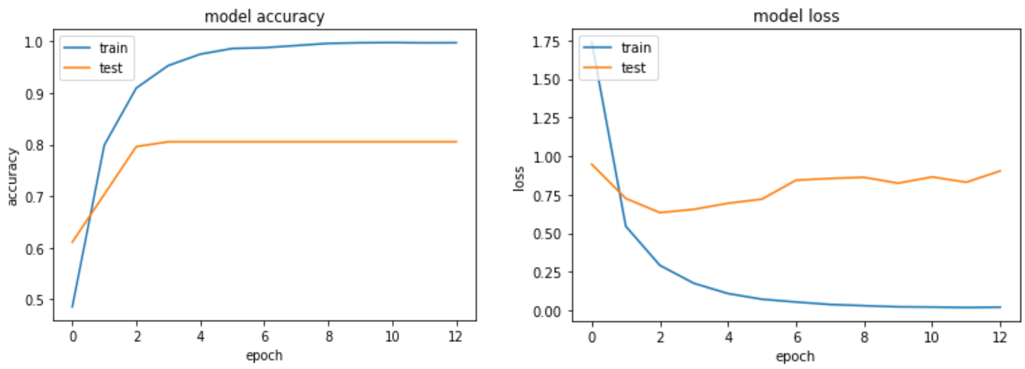

Figure 6 : Model 1 Accuracy and Loss graph

In the model accuracy graph, the accuracy suddenly increases between epochs 0 and 2 as it learns faster and then stays constant, as shown by the train curve. From 0 to 2 epoch, the test curve increases linearly; thereafter, it remains constant and provides an accuracy of 80.5%.

The train curve in the model loss graph rapidly declines from 0 to 1 epoch and then stays constant after 2 epoch starting from 175% and declining to almost 0%. From 0 to 2 epoch, the test curve declines, and after that, there is a tiny increase and linearity in the loss which starts from 100% and goes until 90%.

Model 2 :

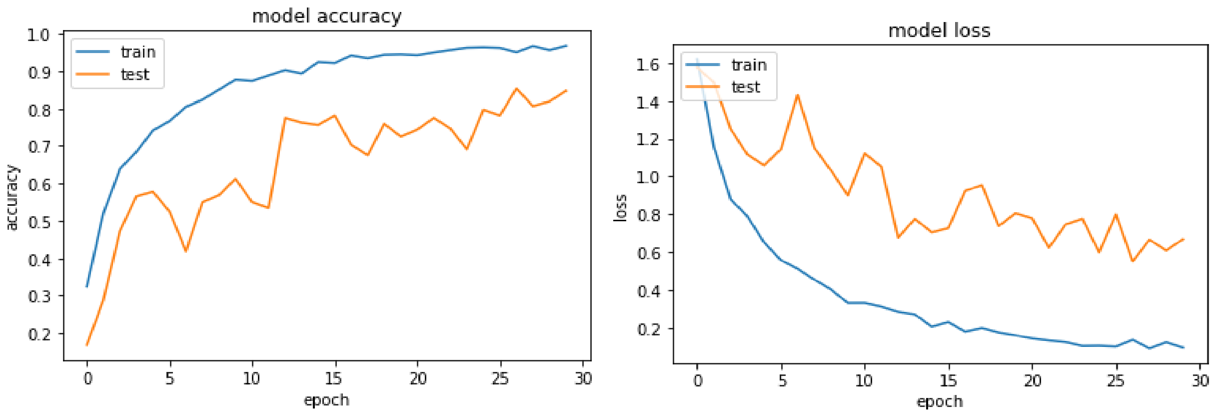

Figure 7: Model 2 Accuracy and Loss graph

According to the train curve in the model accuracy graph, there is a sharp increase in accuracy between epochs 0 and 5, followed by a slight increase and then a nearly constant accuracy thereafter. The test curve grows sharply from 0 to 3 epoch; following that, it declines at 5 epoch, and this pattern of increase and reduction is seen in subsequent epochs, providing an accuracy of 80.5%.

From 0 to 3 epoch, the train curve in the model loss graph rapidly declines, then it keeps declining and nearly stays constant after that, starting from 160% and decreasing to almost 0%. The test curve declines from 0 to 4 epoch, and then, at 4 to 7 epoch, there is a dramatic surge in the loss curve. For an extended period of time, this pattern persists, starting from 160% and decreasing till 70%.

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Model 3:

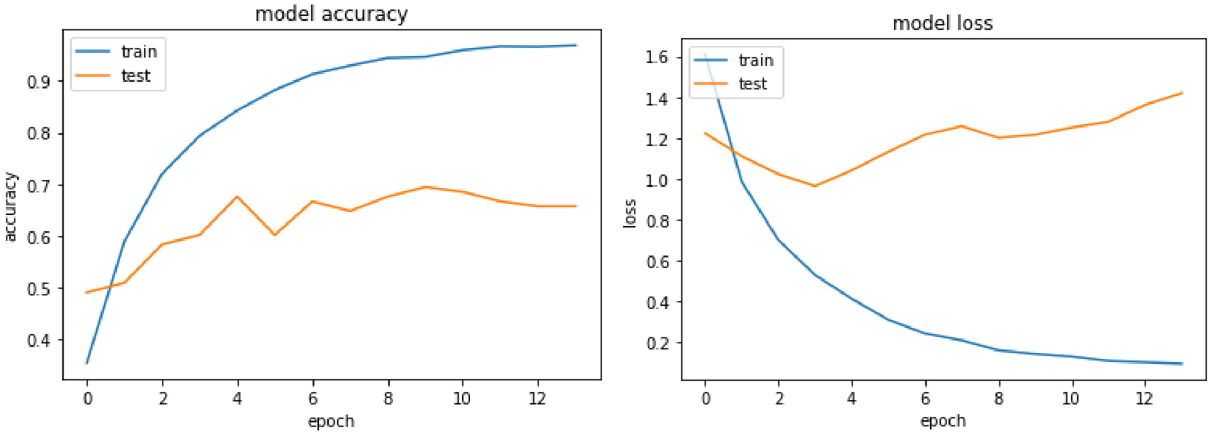

Figure 8: Model 3 Accuracy and Loss graph

The train curve in the model accuracy graph demonstrates how the accuracy abruptly rises between epochs 0 and 2 and then continues to rise after that. The test curve rises from 0 to 3 epoch; after that, at 3 epoch, the accuracy rises sharply, and the pattern of growth and drop is seen in subsequent epochs, providing an accuracy of 65%.

From 0 to 4 epoch, the train curve in the model loss graph rapidly declines, continues to decline, and then remains almost unchanged thereafter, starting from 160% and decreasing to almost 0%. The test curve decreases from epoch 0 to epoch 3, and then the loss curve increases for subsequent epochs, starting from 120% and going high till 140%.

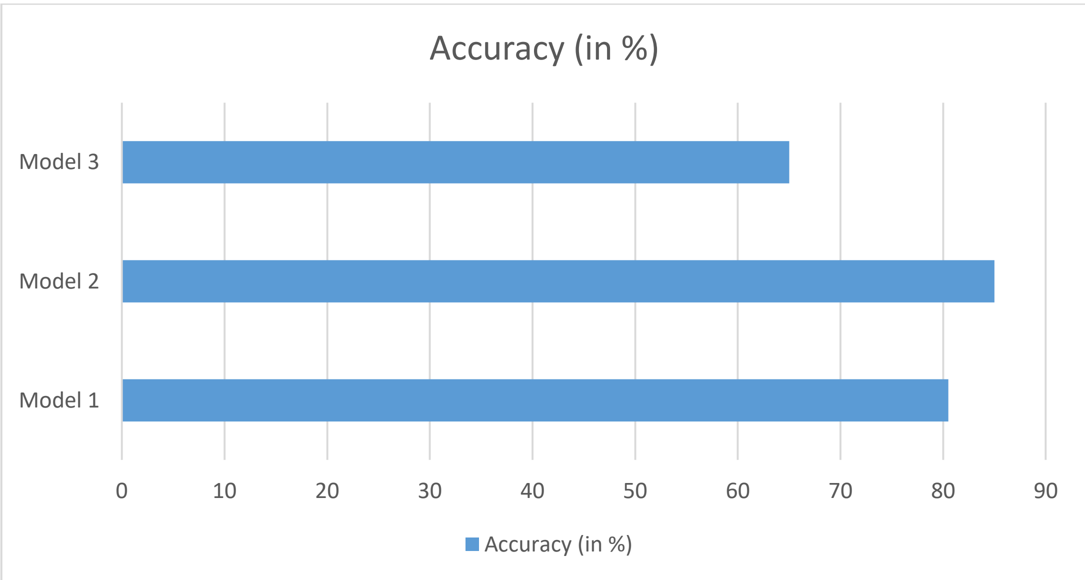

Figure 9: Comparison of accuracy of all 3 models

VI. CONCLUSION

This work offers thorough understanding of machine learning methods for categorizing skin conditions. The algorithm must be utilized by the healthcare industry if the results are to be used for sickness identification. We used a CNN-based algorithm to locate and identify the skin disease. After training them on data pertaining to skin illnesses, we used these models to identify diseases. A system was seen to predict the diseases with an accuracy of around 74% - 75%.[17] The accuracy of proposed Model 1 was 80.5%, that of Model 2 was 85%, and that of Model 3 was 65% in this paper. This exhibits CNN's capability to extract key elements for skin disease detection. The results clearly show that the model generates reliable results. By increasing the training set's size and adding more variance, accuracy can be improved. Keep in mind that the images that the networks have retrieved are very similar to the actual scene. In order to boost precision, it could be necessary to create a hierarchical categorization algorithm using the photos we've already received. Therefore, compared to previous models, predictions can be made more frequently by combining ensemble characteristics and deep learning. Convolution neural networks are found to perform well.

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