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CONVOLUTIONAL NEURAL NETWORKS: A DEEP LEARNING-BASED SKIN DISEASE DETECTION (CNN)

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Abstract
One prevalent human health issue that has a significant impact on people's lives is skin disease. Patients can recover more quickly if they receive timely therapy after receiving an early and correct diagnosis of their illness. Recent advancements in convolutional neural networks (CNN) based on deep learning have greatly increased the accuracy of illness categorization. Inspired by that, this study used deep CNN architectures to identify two skin conditions: psoriasis and eczema. Tenfold cross validation has been utilized to evaluate the performance of five distinct cutting-edge CNN architectures. With the Adam optimizer, the Inception ResNet v2 architecture has achieved a maximum validation accuracy of 97.1%. The results of the performance matrices suggest that the model does a really good job of diagnosing skin conditions. Furthermore, the research illustrates two methods for putting the implemented model into practice. (i) A method focused on smartphones: It incorporates CNN models into the mobile app, (ii) Web server based approach: It combines a web server and CNN model to classify skin diseases in real time.

Keywords: CNN, Web server, ResNet, Deep Learning, Adam Optimizer

1.INTRODUCTION

One of the biggest and most noticeable organs in the body, skin serves as a barrier against heat, injury, and other harm that ultraviolet radiation may bring. Sadly, more than 900 million individuals suffer from different kinds of skin conditions. Skin disease is therefore one of the most common illnesses in the modern world. There are several skin conditions that might cause pain or no problems at all. Some skin problems are minor, while others can be fatal. Some have situational origins, such as pollution from the environment, while others may be inherited. Correctly identifying skin disorders can be crucial given the range of factors that affect disease occurrence. Despite the fact that skin conditions are not always treatable, try to lessen the symptoms. It is challenging to adequately evaluate and assess skin diseases due to the unevenness, tone, presence of hair, and other features of the skin. Despite being one of the most prevalent malignancies nowadays, skin cancer is usually preventable. Preventing the severity of skin disorders requires early and precise diagnosis. CNN models based on deep learning have advanced recently, greatly enhancing the classification process. Therefore, the purpose of this work is to use deep learning techniques to identify two prevalent skin illnesses.

Children frequently suffer from atopic dermatitis, also known as eczema, which causes red, itchy skin [1]. It is a chronic illness that flares up from time to time and might be accompanied with hay fever or asthma. Another frequent skin condition is psoriasis, which can develop anywhere but usually affects the outside of the elbows, knees, or scalp [2]. According to some people, psoriasis causes burning, stinging, and itching sensations. Other medical disorders including diabetes, heart disease, and depression can occasionally coexist with it. The purpose of this research is to classify two prevalent illnesses, psoriasis and eczema, by identifying their characteristics.

2.LITERATURE REVIEW

Skin diseases are becoming far more common among people. Many machine learning and deep learning techniques and models have been suggested by various researchers over the years for the detection of skin disorders. A method for diagnosing psoriasis based on skin color and texture characteristics obtained from the Gray Level Co-occurrence Matrix (GLCM) was developed by Abbadi et al. [3]. In order to distinguish between input photos of psoriasis that is infected and those that are not, feed-forward neural networks have been employed. Połap et al.'s study [4] suggested a sensor-based intelligent skin disease detection system that can recognize skin conditions just by looking at camera video. With an allowable training accuracy of 82.4%, their suggested CNN architecture exhibits encouraging results. Given how expensive and time-consuming it is to diagnose skin diseases, In [5], a methodology for automatically detecting and measuring the severity of eczema is presented. The suggested approach can identify the eczema-infected regions based on the color and textural features of the picture. The detected areas are categorized as mild or severe using the Support Vector Machine (SVM) classifier. Similarly, chronic kidney disease has been identified using a variety of machine learning classifiers at [6]. The study was conducted on a dataset of chronic renal disease where at 99.1%, Naive Bayes had the best classification accuracy. A reduced dataset with varying quantities of characteristics was used for the experiment. The dataset characteristics were eliminated while taking into account certain criteria, which ultimately improved the classification accuracy.

Abdulbaki et al. have presented an architecture based on cloud computing [7]. This article uses a Back-propagation Neural Network (BpNN) in conjunction with cloud computing to diagnose eczema. A CNN architecture based on transfer learning was developed by Janoria et al. [8] to identify different types of skin cancer. While machine learning classifiers have been used to diagnose illnesses, CNN was utilized to extract characteristics from the pictures. The K-Nearest Neighbor method in the VGG-16 CNN model produced the highest accuracy of 99%, according to the experimental study. The performance of several machine learning techniques using Convolutional Neural Networks (CNNs) was examined in the study of Bhadula et al. [9]. With a training and testing accuracy of, the CNN model performed better than any other machine learning technique. 96% and 99.1%, in that order. A CNN design was suggested by Shanthi et al. [10] for the automated diagnosis of skin conditions. Eleven layers make up the suggested model, which includes a softmax classifier, pooling, activation layer, and multiple convolution. According to the experimental research, the suggested model's accuracy was around 99%. Similar CNN models have been proposed for the diagnosis of Alzheimer's illness [14], renal disease [11], heart disease [12], and rice plant disease [13].

3.METHODOLOGY

The specifics of the skin disease detection procedure and several CNN models are covered in this section under the relevant subheadings. The specifics of the working process are depicted in Figure 1. Data gathering and picture classification are the first steps in the process. After that, noisy data is eliminated and the photos are downsized. The purpose of image augmentation is to expand the dataset. CNN models are then used to extract the features, and classification is completed at the end.

3.1 Dataset Collection

One of the biggest and most obvious organs that aids in living is the skin, however regrettably, 900 million individuals worldwide suffer from various skin conditions. Skin disorders can range from minor to potentially fatal. Psoriasis and atopic dermatitis (also known as eczema) are two prevalent skin conditions that we have examined in our study. Images of the disease-affected skin were gathered from the following sources:

1. DermNet NZ [15]
2. IOWA Health Care University [16]
3. Atlas of Dermatological Skin Disease [15].

Following picture collection, we manually selected and eliminated a few low contrast, noisy photos from the dataset, creating a dataset of 1000 photographs of diseased skin, including 490 images of eczema and 510 images of psoriasis. We obtained a fully representative collection of photos for every disease class by collecting sample skin disease photographs of various body sections. Fig. 2 displays sample dataset photos.

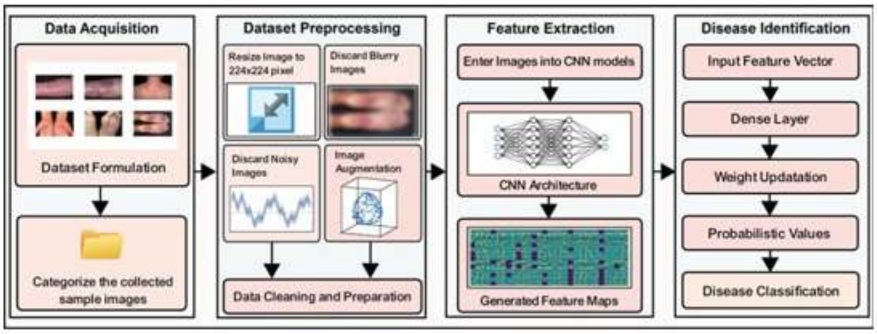


Fig1: The deep learning-based skin disease prediction model's operational process involves gathering data first, then classifying it. CNN architectures are used to extract features and carry out various data pre-processing and cleaning procedures. Lastly, CNN's thick layer is used to carry out the classification.

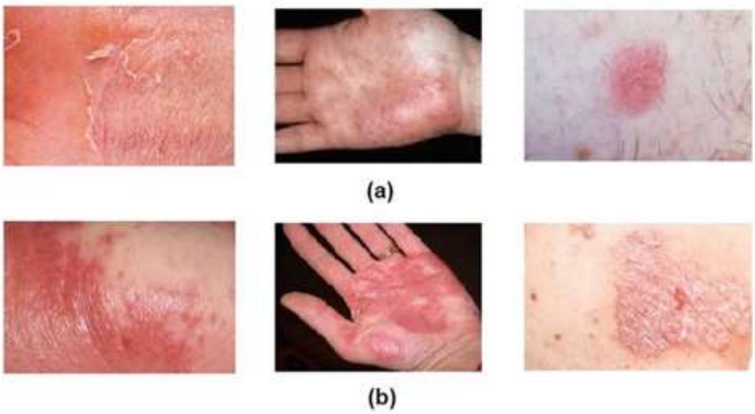


Fig2: Sample images of our skin disease dataset, **a** Eczema, **b** Psoriasis

Table 1 Total training and validation images after augmentation process

Disease type	Before augmentation	After augmentation	Training data	Validation data
Eczema	490	2940	2352	588
Psoriasis	510	3060	2448	612
Total	1000	6000	4800	1200

3.2 Data Augmentation

Data augmentation is crucial in reducing the over-fitting issue since it allows practitioners to greatly expand the variety of data available for model training without having to gather additional data. Our dataset has been enhanced using data augmentation techniques such horizontal flipping, random rotation of 5 ◦C, brightness enhancement of 20%, and contrast enhancement of 10% in order to improve interaction and account for all potential changes. We produced five distinct enhanced versions of each example image in this manner. The number of dataset pictures following the augmentation procedure is displayed in Table 1.

For training and validation data, we have employed an 80-20 data split. Consequently, we have 1200 validation photos and 4800 training images. For testing, we used 400 photos of skin conditions that were gathered from the Internet. Similar features to the training photos are present in these testing photographs. To eliminate any bias, the test pictures were completely separated from the training and validation data.

3.3 CNN Architectures

Using labeled data with their corresponding classes as training data, convolutional neural networks are supervised machine learning algorithms that specify picture recognition and classification. Five distinct CNN architectures were chosen for our investigation based on a number of factors.

The VGG-16 [17] architecture is a highly deep CNN model with a huge parameter size and 3 × 3 filters throughout. The model's accuracy in the imagenet dataset was high. Similar to the VGG-16, the Inception v3 [18] design is a deep CNN architecture; however, it offers great accuracy with a substantially smaller parameter size because to the Inception module. Within the model, the ResNet-50 [19] design has residual connections. The ResNet-50 design uses such residual connections to solve the over-fitting issue. The depthwise separable architecture of MobileNet v2 [20] convolutions, which speed up the classification process and decrease the size of the parameters. Because of its tiny parameter size, this architecture offers a significant level of accuracy in imagenet datasets and is especially helpful for merging CNN models with mobile apps. Beginning ResNet-v2 [21]architecture integrates the residual connections with the inception module. Compared to the initial model, which had more accuracy in classifying several classes, this is an improvement. Thus, we tested these designs using our dataset to see how well they functioned under various criteria. The last dense layer of the CNN architectures was unfrozen while all other layer weights were frozen as part of our fine-tuning technique for training the designs. Next, we initialized random weights to the nodes and trained the dense layer using our dataset of skin diseases.

3.4 Optimization Algorithms

Optimizers are algorithms that alter CNN architectures' weights and learning rates in order to increase accuracy. Adam [22] and Rmsprop [23] are the two optimizers that we employed in our study. First and second order momentum are used by Adam (Adaptive Moment Estimation) [22]. For every parameter, Adam calculates adaptive learning rates. Adam keeps the average past gradients exponentially in addition to an exponentially fading average past gradients like Rmsprop. Eqs. 1 and 2 define the past decaying averages and past squared gradients, Pt and Qt, respectively.

$$P_t = \beta_1 P_{t-1} + (1 - \beta_1) g_t \quad (1)$$

$$Q_t = \beta_2 Q_{t-1} + (1 - \beta_1) g_t^2 \quad (2)$$

Here, P_t and Q_t represents the estimated mean and uncentered variance of the gra- dients, respectively. The P_t and Q_t are biased toward zeros because of initial time steps and small decaying rates. Hence the corrected bias is calculated as

$$\hat{P}_t = \frac{P_t}{1 - \beta_1^t} \quad (3)$$

$$\hat{Q}_t = \frac{Q_t}{1 - \beta_2^t} \quad (4)$$

Finally, for updating the weights considering η step size, the weight W_t is calculated as,

$$W_t = W_{t-1} - \frac{\eta}{\sqrt{\hat{Q}_t} + \varepsilon} \hat{P}_t \quad (5)$$

By default, β1, β2, and ε have values of 0.9, 0.999, and 10−8, respectively. In this manner, the Adam optimizer takes average previous gradients into account while updating the node weights.

A decaying average of partial gradients is used by Rmsprop, another weight updating technique, to adjust the step size for every parameter [23]. Early gradients can be forgotten by the algorithm thanks to the declining average of partial gradients. and concentrate on the most recently noticed partial gradients as the weight update process moves forward, which facilitates rapid convergence. For any weight A(g2), the squared gradient average is computed as follows:

$$A(g^2_t) = 0.9A(g^2_{t-1}) + 0.1\, g^2_t \tag{6}$$

For updating the weights considering η step size, the weight V_{t+1} is calculated as,

$$V_{t+1} = V_t - \frac{\eta}{\sqrt{A(g^2_t) + \varepsilon}} g_t \tag{7}$$

The default values for η and ε are 0.001 and 10^{-8}, respectively.

4. RESULTS

4.1 Experimental Setup

A computer with an Intel Core i7 CPU, 16 GB of RAM, and Nvidia Gtx-1060 graphics was used for the experiment. The models have been collaboratively trained using the Keras framework with a TensorFlow back-end to do the classification. The dataset has been split 80/20 for training and 20/20 for validation. 400 photos in all have been taken into consideration for model testing. The training and validation method has taken into account 100 epochs of 10-fold cross validation. The weights have been updated using the RmsProp and Adam optimizer algorithms. The binary cross entropy loss function has been utilized because our dataset only includes two classes. The following hyperparameters were employed in our experiment:

Input Image Size: 224×224
Epoch: 100
learning rate: 0.001
Classification: Softmax
Momentum: 0.9
Optimizer: Adam, RmsProp

4.2 CNN Performance

Initially, the CNN structures are fed the input pictures. Multiple convolution and pooling layers make up each CNN model. The input photos are transformed into feature vectors by each of these layers. Fig. 3 displays the feature maps of representative photos of psoriasis and eczema.

For the classification procedure, we employed a fine-tuning technique in which we frozen every CNN architecture layer save the last dense layer. Adam and the Rmsprop optimizer were used to update the weight in the final dense layer. Table 2 displays the comprehensive experimental outcomes of several CNN designs.

According to the results shown in Table 2, Adam and Rmsprop optimizer both did a comparable job of identifying the skin conditions. Adam accomplished the great accuracy in testing, validation, and training. However, Adam and Rmsprop performed exactly the same in the overall case.

The training, validation, and testing accuracy bar graph of several CNN architectures is shown in Figure 4. The Inception ResNet v2 architecture with Adam optimizer produced the best training, validation, and testing accuracy, according to the experimental study.
Additionally, the MobileNet v2 architecture significantly effectively with a reduced parameter size. Over 90% training and validation accuracy was attained by both VGG-16 and Inception v3. Both the Adam and Rmsprop optimizers displayed over-fitting features in the ResNet-50 architecture. Although it performed poorly on validation and testing data, it attained great accuracy throughout the training phase. The confusion matrix on the testing dataset and the accuracy curve of the training and validation data using the Inception ResNet v2 architecture are shown in Fig. 5 since the Inception ResNet v2 architecture with Adam optimizer obtained the best overall accuracy.

We can observe from the confusion matrix in Figure 5a that the Inception ResNet v2 architecture accurately and very precisely recognized the test set. The training and validation curves are shown in Fig. 5b, where the accuracy curve progressively rose. and no indications of over-fitting traits are seen. The curve achieved its ideal level after 80 iterations. It is clear from the validation and testing accuracy that the Inception ResNet v2 architecture identified the skin conditions accurately.

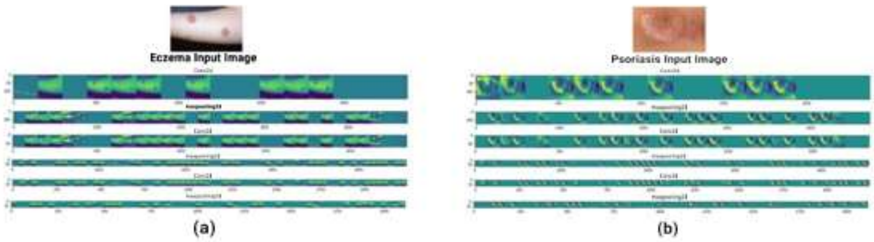


Fig. 3 Feature maps generated from input skin disease image. Here **a** illustrates the original eczema disease image followed by the feature maps generated by multiple convolution and pooling layer, **b** illustrates the original psoriasis disease image followed by the feature maps generated by multiple convolution and pooling layer

Table 2 Accuracy metrics of various CNN architectures using Adam and RmsProp optimizer

Architecture	Training accuracy	Validation accuracy	Testing accuracy	Parameter size (millions)
		Adam optimizer		
VGG-16	98.7	95.8	93.5	134
Inception v3	97.7	91.3	85.6	23
Resnet-50	86.1	72.3	69.8	25
MobileNet v2	99.3	96.3	95.1	**3.5**
Inception ResNet-v2	**99.7**	**97.1**	**95.8**	55
		RmsProp optimizer		
VGG-16	99.4	95.2	91.8	134
Inception v3	98.1	90.5	86.0	23
Resnet-50	87.5	75.8	70.1	25
MobileNet v2	99.2	95.7	94.0	**3.5**
Inception ResNet-v2	99.3	96.5	94.3	55

Here bold font indicates best result

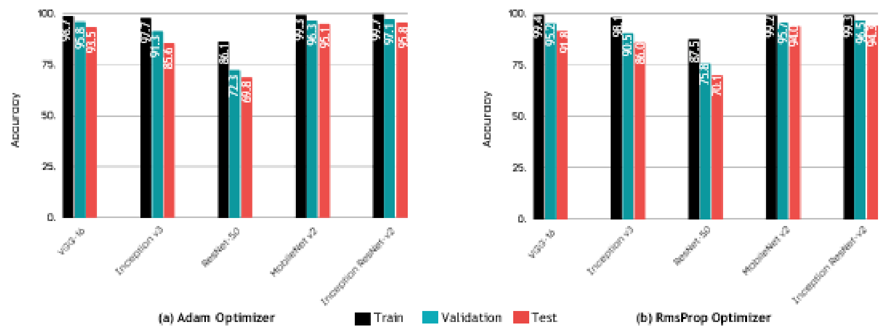


Fig. 4 Accuracy graph of various CNN architectures. Here **a** represents the accuracy graph using Adam optimizer, **b** represents the accuracy graph using RmsProp optimizer

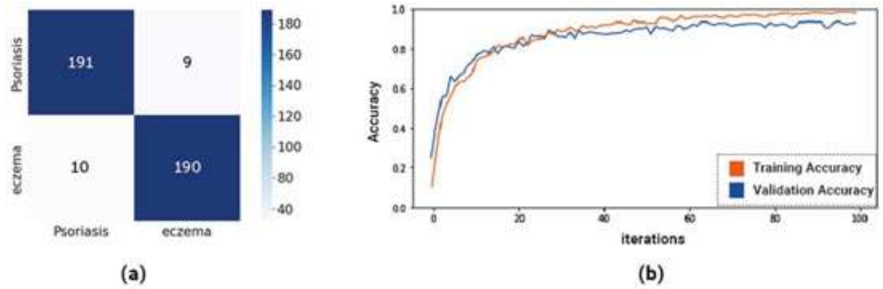


Fig. 5 Inception ResNet v2 architecture performance with Adam optimizer. Here **a** represents the confusion matrix on testing dataset, **b** represents the training and validation accuracy curve

Table 3 Comparison of proposed model with existing work

Author	Proposed method	No. of Disease	Performance
Abbadi [3]	GLCM feature extraction with feed forward neural network	1 (psoriasis)	All samples are detected correctly
Srivastava [5]	Neural Network model to identify eczema using texture feature	1 (eczema)	90% accuracy on testing dataset
Bhadula [9]	Machine learning classifiers based approach	3 (acne, lichen planus, sjs ten)	96% accuracy on testing dataset
Shanthi [10]	CNN based classification approach	4 (Acne, Keratosis, Eczema, Urticaria)	Accuracy: 98.6–99.04%
Proposed model	Inception ResNet-v2 architecture combined with Adam optimizer	2 (eczema, psoriasis)	Training: 99.7% Validation: 97.1% Testing: 95.8%

4.3 Discussions

Numerous researchers have put forth alternative approaches to identify various skin conditions. Table 3 displays our suggested approach along with a statistical comparison of other research. Because different skin diseases have distinct forms and colors, we can see from the findings in Table 3 that the majority of the efforts concentrated on the feature and texture selection procedure. Additionally, the accuracy of the majority of CNN techniques was comparable.

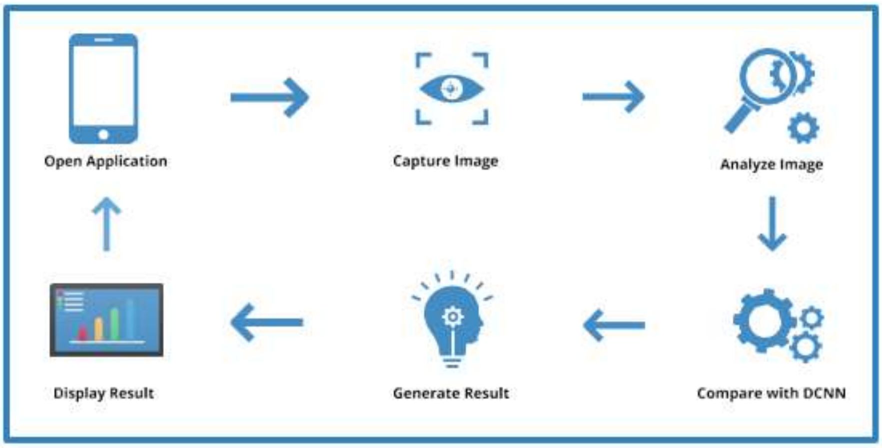
The following observations are derived from the experimental study of the skin disease dataset:
1. Any CNN model's accuracy on a given dataset may be greatly increased using the fine tuning approach as opposed to the transfer learning method.
2. The Adam optimizer outperformed the Rmsprop optimizer in terms of execution time. Rmsprop The categorization assignment took longer for the optimizer to complete.
3. Using the Adam optimizer, the Inception ResNet v2 architecture produced the best training, validation, and testing accuracy.
4. Using 15 times fewer parameters, the MobileNet v2 architecture achieved accuracy comparable to that of the Inception ResNet v2 design.
5. Adam and the Rmsprop optimizer both had comparable accuracy results. As a result, both optimizers may be applied to classification tasks.
6. Both the Adam and Rmsprop optimizers displayed over-fitting traits with the ResNet-50 design.
7. The weights are updated more effectively with a learning rate of 0.001 and momentum of 0.9. 0.0001 and 0.01 learning rates, however, also showed comparable results.

5. **Practical Applications**

5.1 Smart Phone Oriented Approach

Mobile devices are currently among the most popular communication and data transmission tools due to their exponential increase in quantity and accessibility globally. Since almost everyone has a mobile device these days, scanning skin photos and getting results instantaneously would be simple for the user. To quickly identify skin conditions, the CNN model may be included into a mobile application. Fig. 6 shows the framework for mobile applications.

The CNN models are initially frozen with the optimizer's updated weights in order to apply the application. The Android application is then merged with the CNN model that has been frozen. A lightweight model is preferred for mobile devices, hence the MobileNet v2 architecture is better suited to carrying out the the application's categorization task. The findings are shown to the user when the user snaps a photo using the mobile app and compares it to the stored CNN model.



z **Fig. 6** Smartphone oriented framework for skin disease detection

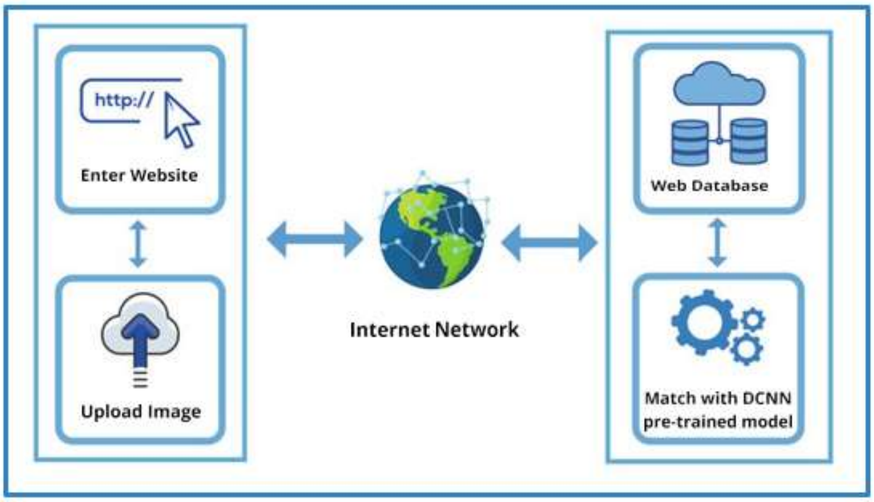


Fig. 7 Web server oriented framework for skin disease detection

5.2 Web server oriented Approach

Due to their resilience and variety, websites are also widely utilized by consumers in addition to mobile devices. A web server is capable of handling and storing far more complex data than a mobile device. Therefore, for a rapid and precise illness diagnosis, a web-based skin disease detection system may be a useful option. We can use huge CNN models on web-based servers, which improves the effectiveness of the illness detection process, but we can only utilize lightweight CNN models on mobile devices. Fig. 7 displays the suggested web server-oriented structure for detecting skin diseases.

The pre-trained deep CNN models must be stored in the web database in order to deploy the web server-based detection system. The front end is where users sign in. uploads the pictures of the skin condition on the internet. The submitted photographs are then compared to the CNN model stored in the online database. Lastly, users are shown the results that match. This allows consumers to receive the correct diagnosis in real time.

6. CONCLUSION

Medical science will advance on a larger scale with the aid of disease detection and computational support. In order to identify two prevalent skin illnesses, psoriasis and eczema, we suggested deep learning-based skin disease detection techniques in this study employing several CNN architectures. Five distinct CNN architectures were trained using the Adam and Rmsprop optimizers and the fine tuning technique. Of all Inception of CNN architectures With validation and testing accuracy of 97.1% and 95.8%, respectively, the ResNet v2 architecture fared better than any of the previous CNN designs. Lastly, two strategies for the real-world implementation have been shown: (i) a smartphone-oriented strategy and (ii) a web server-oriented strategy. These practical applications are useful for diagnosing and determining the severity of the condition in real time.

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