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Robust Model for Skin Disease Classification using Deep Learning Techniques

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The most common causes of skin problems include fungi, germs, allergies, viruses, laser technology, and accurate identification of skin diseases is done by medical technology based on photonics. Such diagnosis is difficult and costly to accomplish with the current medical technology. The application of deep learning algorithms is crucial in the skin disease classification process. Data reconstruction and manual feature extraction for classification purposes are two examples of how deep learning (DL) algorithms have cut down on human work. Random Forests (RFs), Support Vector Machines (SVMs), K-Nearest Neighbors (K-NNs), Convolutional Neural Networks (CNNs), etc., are just a few of the deep learning and machine learning methods that have been utilized by researchers for the purpose of skin disease classification. This study compared VGG16 and Convolutional Neural Networks (CNNs) performance on keras environment for skin disease classification to previous work by other researchers and found that the proposed method achieved better accuracy. Tuning the CNN and VGG16 models using various tuning parameters, such as a convolutional layer with pooling and dropout, as well as filter, kernel size, and neuron count, is the major role of this research study. In the 15th epoch, both the suggested CNN model and VGG16 had reached 99% and 100% of training accuracy, respectively. Similarly CNN and VGG16 had reached 96% and 97% of testing accuracy respectively. The suggested VGG16 model outperforms its competitors, according on the experimental data.

Keywords: Skin disease, Classification, Deep learning, KERAS, CNN, and VGG16.

1. Introduction

Currently, people are suffering from so many diseases due to the increasing population, uncleanness and some are due to viruses. Dermatology is also a cause of skin cancer and one of the major problems in all these. Dermatological illnesses represent a challenging field of science due to the complex processes involved in disease diagnosis and their variability in response to environmental changes. Dermatological conditions are the most prevalent, particularly those vulnerable to spread, and can be fatal perhaps resulting in skin cancer if not treated in the first stages. The main problem with this disease is that people or sometimes doctors are not getting the proper cause for skin cancer due to lake of technology. Anyhow if we can get a proper technology that will easily identify the root cause of this disease and help the doctors for the treatment of patients, then we can control this problem. Here we got the biggest motivation to work in this field. Then we started searching for a technology that will detect and rectify skin cancer disease. Currently, we can see that the number of patients is going to decrease, this is due to novel DL and ML based technology. This research primarily contributes by developing a robust CNN and a revolutionary VGG16-based deep learning model that achieved superior accuracy compared to previously established models for classification of skin cancer classification [16][3][22]20[10][18] [7]5[11][9]. Deep Learning (DL) based models are popular choice with various image based data in various domains where images based large volume of data analysis is a crucial and challenging task. However, we have recently expanded our focus to include skin cancer illness classification as a domain where we have implemented a deep learning based CNN and VGG16 tuned model. This model has proven to be highly effective in classifying various skin cancer diseases.

Many authors worked in the field of classification of skin disease using ML and DL technques and achieved satisfactory levels of accuracy. This research work used DL based classification model for skin diseases classiication. In this research work, CNN and VGG16 models are used, and accuracy rate of the proposed system with traditional CNN and VGG16 with keras have achieved an accuracy of 96 % and 97% respectively. Authors

[16] suggested CNN model for the classification of five different skin disease images. They collected dermatology images from Dermnet website. The proposed CNN based model used a large data set and obtained an accuracy rate of up to 90%.

According to the authors [17], CNNs, VGG, ResNet, , Inception, , MobileNet, Dense Convolutional Network, Inception-ResNet and Neural Network Search Network have all been employed as resource extractors. SVM, Bayes, MLP, RF, and KNN are the classifiers utilized for injury categorization. In this paper author analyzed and diagnosis skin lesions based on Melanomas, atypical nevi and common nevi. Here dataset taken from ISBI-ISIC and the PH2. Both the KNN classifier and the DenseNet201 extraction model reached very high levels of accuracy: 93.167% and 96.805%, respectively. As a result, the technique is dependable and effective for physicians who support skin disease diagnosis.

Authors[3] used Harvard’s HAM (Human Against Machine) dataset that creates a sequential model by using Keras and developed a CNN model that achieved 82% of accuracy. The authors [8] introduced a mobile dermatological detection program utilizing image processing, which operates effectively in remote regions. A real- time skin disease identification method based on accuracy was developed using deep learning and image processing. Authors[22] focused on proposed model for dermatology categarization using CNN method. This experimental was conducted on a publicly available dataset of skin disease images, demonstrating that the CNN model classifies dermatological images with an accuracy of 79.29%. However, when integrating the proposed model that utilizes the patient's background knowledge in the modeling process, the accuracy improves to 80.39%. Authors [12] used a feature extraction method that performed an important role in the classification of dermatology. Authors [20] developed an automated skin lesion analyzer for affected skin lesion images and classify 6 different types of skin disease. They worked with 5000 skin disease images. The proposed classifier classifies skin diseases with a 95% accuracy. Authors [10] proposed a system that was able to classify the 10 most common skin diseases efficiently. They used 3099 datasets as training samples and 595 datasets as a testing sample and over all the proposed model achieved 90% accuracy. Authors [19] developed a model for skin diseases classification, and used Mobilenet, and VGG-16 deep learning model and designed a custom model with the help of these models. This model was embedded in skin lesion analyzer machines and the author got above 80% of accuracy.

Authors[23] presented a system utilizing CNN that incorporates three established deep learning methodologies: AlexNet, ResNet, and InceptionV3.A dataset comprises seven skin disorders utilized for the classification of skin conditions. The dataset was augmented with photos of cuts and burns, which are predominantly categorized as skin illnesses by the majority of current systems. The application of DL algorithms diminished the necessity for human labor, for classification, achieving 64.62% accuracy using ResNet15 on a Python platform over 40 epochs. Authors [1] employed a hybrid feature extraction technique that included 2-dimensional discrete wavelet transform (2D-DWT) together with geometric and textural characteristics for both feature extraction and segmentation. The categorization is performed using a DL method utilizing CNN to efficiently forecast skin diseases. The experimental study utilized the ISIC database.

Authors [14] developed a novel GLCM algorithm that give a better and more efficient classification accuracy with dermatology dataset. They compared accuracy between two supervised machine learning namely KNN and SVM where KNN achieved 98.2% accuracy with wise-Geek group dataset. Authors [15] proposed ResNet and CNN to predict dermatology lesions and got 77% and 68% accuracy with CNN and ResNet respectively. Many authors have used another deep learning method like VGG16 for the classification of skin diseases. Authors [11] proposed combined model of VGG16 and LSTM and achieved 95.62% of accuracy. Authors[4] used both machine and deep learning techniques for the skin disease categorization and compared the performance of both where the Bagged Tree Ensemble method gives 92% accuracy, KNN gives 92%, SVM gives 83%, VGG16 gives 63.45%, GoogleNet gives 70.21%, and ResNet50 gives 73.31% of accuracy.

The proposed a hybrid model [7] that is a combination of VGG16 and ResNet-50 for skin lesion classification. This approach consists of ISIC 2016-17 dermoscopic images and achieved 85.65% accuracy. Authors[2] presented VGG16 technique for skin cancer diseases classification. The proposed VGG16 model achieved 89% of accuracy with 10 Epochs on 128 batch sizes with Adam optimizer. An proposed VGG-16 model utilizing a single-level system, alongside a multi-model, MobileNet, and Custom model for skin lesion categorization through deep learning model. The suggested models work with publically available HAM10000 dataset where accuracy was achieved 79.71% in case of VGG-16, 82% in case of MobileNet, and 80.61% in case of Custom Model. Authors [18], suggested a VGG-16 model for the classification of dermatological diseases. They used Dermnet open resource skin disease dataset. They randomly selected 10 skin diseases from dataset and achieved 76% of accuracy.

Authors[24] used photograph ISIC dataset with 69445 skin cancer images. They also compared the performance of different deep learning based classifiers like. Authors [13] proposed the VGG16 model for the skin cancer categorization with ISIC datasets. The authors of [5] employed the VGG 16, ResNet-50 and , Inception_v3 models for the skin lesions classification, where VGG16 obtained accuracy of 96.9%, surpassing the performance of other models. Authors[21] developed a CAD-MD system and evaluated its performance against other advanced classification techniques using the publically accessible PH2 datasets and ISIC 2016 and as benchmark, where the suggested model accurately classifies skin cancer. They suggested [6] VGG 16 model for the classification of skin disease.

2. Methodology and Proposed Architecture

The method represents a critical component of the research work. This section examines the techniques and suggested models for the classification of dermatological conditions. This section also explored the proposed CNN and VGG 16 model in the Keras environment.

2.1 Preprocessing

Data preprocessing is an important phase to build a robust model like duplicates, scaling, resizing, filters, and data imbalance. Data Augmentation is an important preprocessing strategy to improve the performance of model. Various data augmentation methods are used by different researchers like Flip, Brightness and Zoom.

2.2 Keras

Python Software contains the Keras library used in deep learning techniques. The other library of deep learning is Tensorflow [16] which contains various deep learning methods.

2.3 Convolutional Neural Network (CNN)

CNNs are a specialized form of deep learning techniques frequently employed for image processing and categorization. CNN is also useful for video, audio, text, speech, and pattern recognition. CNN consists following layers : Input layer, convolutionallayer, pooling layer, fully-connected layer, and outputlayer. CNN has automatic feature extraction that selects the relevant features from data sources [8].

2.4 Visual Geometry Group (VGG16)

VGG16 is a 16 layer transfer learning architecture. It is one of the popular networks that is similar to LeNet and AlexNet. VGG 16 was the Runner of ILSVRC 2014, ImageNet is one of the challenging competitions that happen every year, and all the researchers are come up with new models to achieve the maximum mechanism were used VGG-16 model [17]. CNN is the different categories in the sense number of convolution layer, number of max pool and number of fully connected layers. VGG 16 is nothing but 16 different layers and these are the layers that can tunable parameters. Other layers don’t contain tunable parameters.

2.5 Proposed Architecture of CNN

CNNs typically comprise several layers, and use various filter sizes for convolutions, depending on the specific architecture and design choices. The proposed CNN model performance may be the same as VGG16 model if the numbers of layers of the CNN model same as VGG16 model as shown in below:

Table 1. The proposed diagram of CNN model is dipicted in Figure 1. It uses KERAS library. This architecture uses four 2D-convolutional layers with dropout and maxpool . It uses 128 neurons with a fully connected layer and 10 neurons with an output layer.

There are the following steps for skin disease image classification using the CNN model:

- Collected skin disease image dataset from the kaggle data science website.
- Divide the skin image dataset into training and testing samples.
- Utilized two convolutional layers, each including 16 filters, with a 'relu' activation function.
- Employed a maximum pooling layer.
- Utilized two convolutional layers, each including 32 filters, with a 'relu' activation function.
- Employed a maximum pooling layer.
- Utilized two convolutional layers, each including 64 filters, with a 'relu' Activation function.
- Employed a maximum pooling layer.
- Utilized a fully linked layer comprising 128 neurons with a 'relu' activation function.

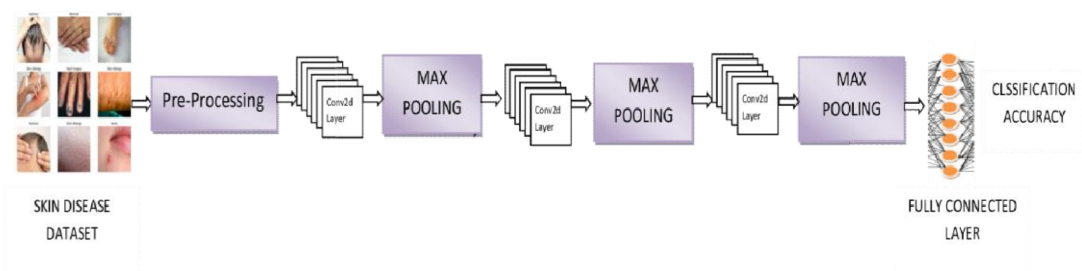

Figure 1: Proposed CNN architecture

The main strength of the proposed CN model is to handle noise-based images with large datasets. The proposed CNN

model handles the noise-based skin cancer images and classifies the large volume of skin cancer images with high accuracy. Since, CNN has properties of automatic feature extraction from images, its relevant feature is extracted from skin cancer images, and it is capable to classify the skin cancer disease-based images. The main drawback of the CNN model is achieving less accuracy in case of small datasets.

2.6 Proposed Architecture of VGG16

The main reason for suggesting VGG16 model is that it has a uniform structure with a fixed number of layers and filter sizes. VGG16 contains fixed 13 convolutional layers and 3 fully connected layers. VGG16 uses only 3x3 filters throughout the network, which contributes to its uniform architecture. Figure 2 dipicts the framework of VGG16 that contains a different number of parameters as mentioned in Table 1. The proposed VGG16 model used 13 Convolution + ReLU layers, 5 Maxpool Layers, and 3 Fully connected Network. The first 2 fully connected layer has 4096 channels. Here, the hidden layer and other layers used ReLU activation function. VGG16 has 1 softmax layer. VGG 16 network accepts color images either acne, nail fungus, hair loss, skin allergy or begin samples with size 180 * 180*3 (3 channels for color). In this network, kernel size is 3*3 with stride 1 throughout all the layers.

The VGG16 model is comprised of two main parts:

- The feature extraction component comprises VGG blocks.
- The classifier component consists of fully connected layers and the output layer.

Table 1: Layers of VGG16 Network Model

Different Layers	No. of Layer
Convolution + ReLU	13
Maxpool Layers	5
Fully connected Network	3
Softmax layer	1

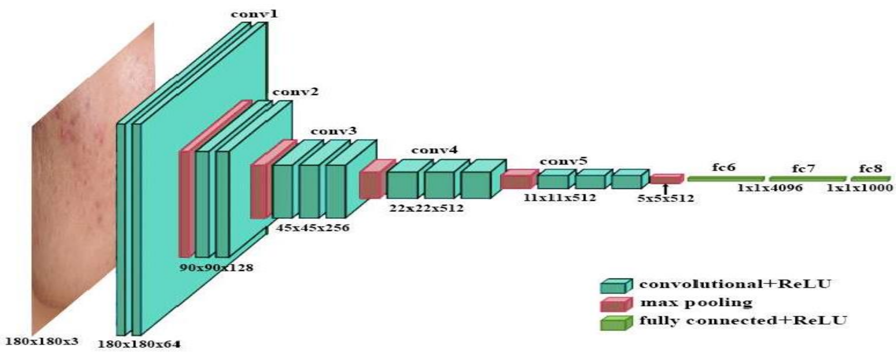

Figure 2: Architecture of VGG16 model

VGG16 is popular due to this simplest property of convolution filter. It also has pre-trained weights on large datasets like ImageNet can be used to initialize the network and fine-tuning can be performed on smaller, task- specific datasets. Particularly when working with limited data, this can greatly enhance performance and speed up training. Object detection and segmentation are only two examples of the many computer vision applications that can benefit from the detailed features that the VGG16 model is able to extract from images. Because there are so many parameters and many convolutional layers are stacked on top of each other,, the proposed VGG16 architecture is relatively computationally expensive. VGG16 can consume a significant amount of memory, both during training and deployment.

3. Dataset

We used the Kaggle data science platform to gather the skin disease image dataset. The collection includes 602 images classified into 5 distinct types. Eighty % images were utilized for training purposes and twenty % were reserved for testing in this study's comprehensive dataset. Both Figure 3 and Figure 4 display samples from the training dataset, one of which contains images of skin diseases and other of which contains images of normal skin.

Figure 3: Sample of training dat set with skin disease images

Figure 4: Sample of training ataset with normal skin images

4. Experimental Analysis

This experiment contains two sections: The first section introduced the CNN model, whereas the next section presented the VGG16 model for skin disease categorization based on accuracy.

Section 1: This section introduced a CNN model for skin diseases classification. Table 2 presents the performance metrics of the suggested model with various measures. The proposed model attained a commendable 99% training accuracy and 96% testing accuracy. Figure 5 illustrates various performance in term of accuracy, and loss of the suggested CNN model. The confusion matrix is essential for calculating several performance metrics. Figure 6 illustrates the confusion matrix of the proposed CNN model. Table 3 presents several performance metrics of proposed CNN model. The many performance metrics assist in evaluating the robustness of model.

Table 2: Performance measures of suggested CNN model with 15 epochs

Proposed Method	Training Accuracy	Testing Accuracy	Validation Accuracy	Training Loss	Validation Loss
CNN	0.99	0.96	0.70	0.02	1.35

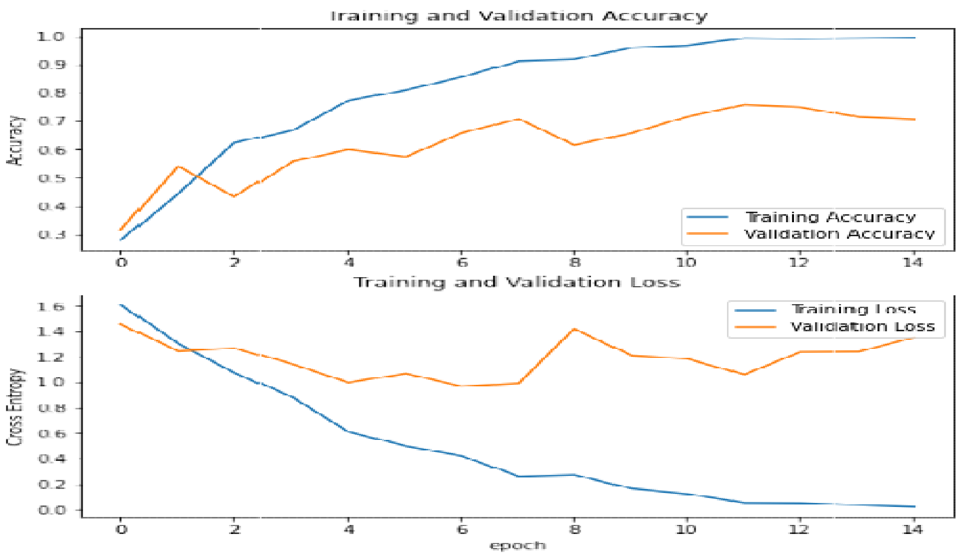

Figure 5: Various measures of the proposed CNN model

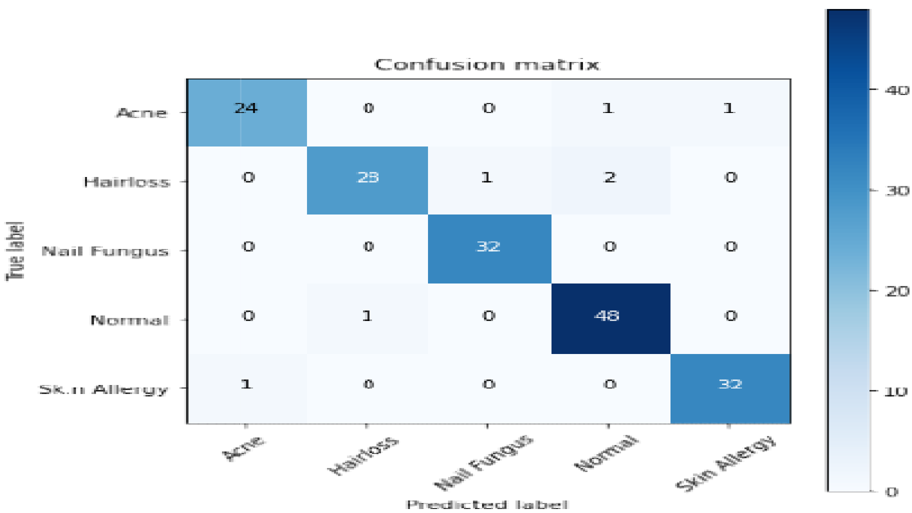

Figure 6: Confusion matrix of suggested CNN model

Table 3: Various performance measures of suggested CNN model

	Precision	Recall	f1-score	support
Acne	0.96	0.92	0.94	26
Hairloss	0.97	0.90	0.93	31
Nail Fungus	0.97	1.00	0.98	32
Normal	0.94	0.98	0.96	49
Skin Allergy	0.97	0.97	0.97	33
macro avg	0.96	0.96	0.96	171
weighted avg	0.96	0.96	0.96	171

Section 2: This section uses VGG16 model for the skin diseases classification. Table 4 shows various metrics of VGG16 model, like training and testing accuracy, validation accuracy, training and testing loss. The suggested VGG16 model attained 100% and 97% training and testing accuracy respectively. Figure 7 illustrates the training and validation accuracy, and training and validation loss, of the suggested VGG16 model. Figure 8 illustrates the confusion matrix of the suggested VGG16 model. Table 5 presents various measures like precision, recall, F-score, and support, for the suggested model. These measures assess the robustness of the VGG16 model.

Table 4: Performance of proposed VGG 16 model with 15 epochs

Proposed Method	Training Accuracy	Testing Accuracy	Validation Accuracy	Training Loss	Validation Loss
VGG16	100	0.97	0.84	3.51	3.57

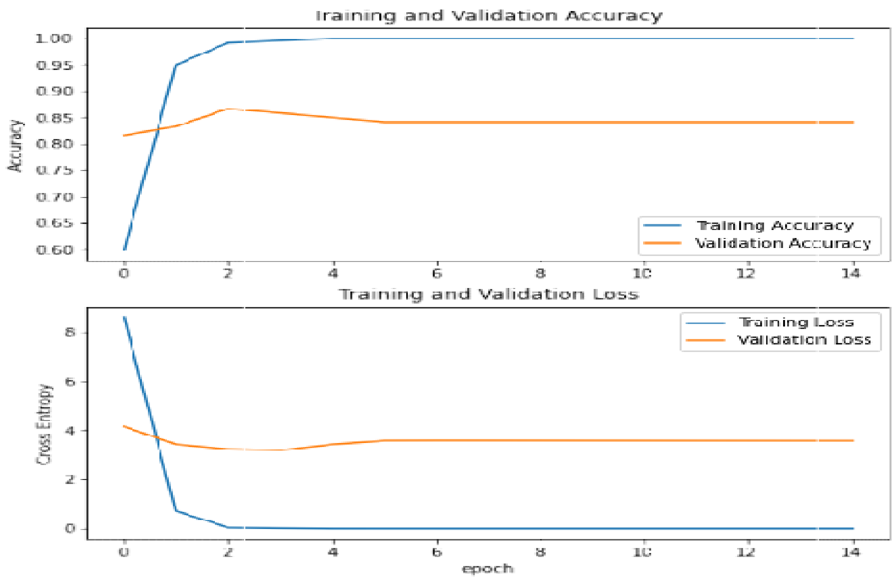

Figure 7: Performannce meaures of proposed VGG16 model

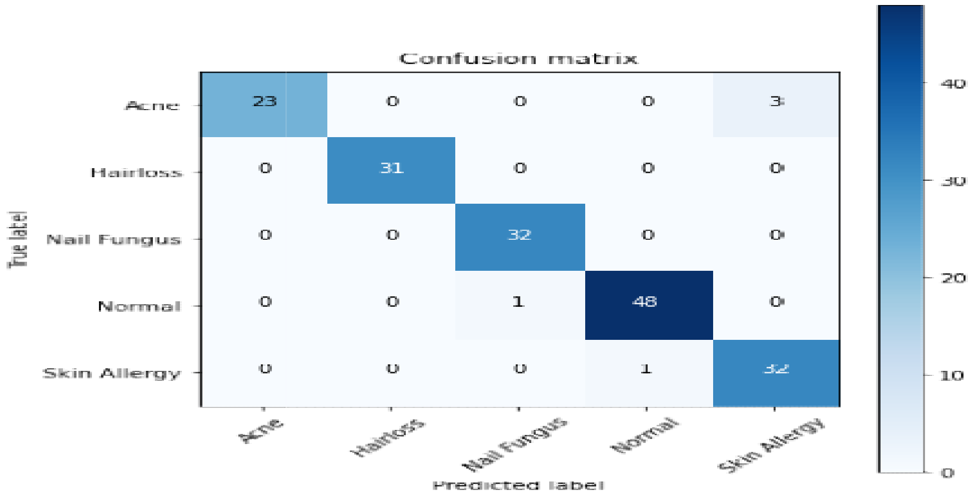

Figure 8: Confusion matrix VGG16 model

Table 5: Performance measures of proposed VGG16 model

	precision	recall	f1-score	Support
Acne	1.00	0.88	0.94	26
Hairloss	1.00	1.00	1.00	31
Nail Fungus	0.97	1.00	0.98	32
Normal	0.98	0.98	0.98	49
Skin Allergy	0.91	0.97	0.94	33
macro avg	0.97	0.97	0.97	171
weighted avg	0.97	0.97	0.97	171

5. Result Analysis

There are different models and frameworks were designed by different researchers using CNN techniques. The CNN model used different tuning parameters like different numbers of neurons, number of epochs, activation function, etc. This research suggested a CNN model for skin cancer disorders categarization. This section compares proposed CNN model with prior models developed by other researchers. Table 6 illustrates and examines the proposed CNN model against others, demonstrating that our CNN deep learning model achieves superior accuracy.

Table 6: Comparison of proposed CNN model with existing models

Reference	Model	Accuracy
[1]	CNN	90%
[2]	CNN	82%
[5]	CNN	80.39%
[7]	Minimal CNN	95%
[8]	CNN	90%
Proposed	Proposed CNN	96.00%

Similarly many authors implemented the VGG16 model with different tuning parameters for the classification of skin cancer diseases. The comparative analysis of our proposed VGG16 model with others where the proposed VGG16 model gives better accuracy. Table 7 depicted that suggested VGG16 model achieved better performance as compared to others.

Table 7: Comparative analysis of the proposed VGG16 model with existing models

Reference	Model	Accuracy
[22]	VGG16+LSTM	95.62%
[17]	VGG16+RESNET 50	85.65%
[24]	Minimal VGG16	79.71%
[13]	VGG16	76%
[19]	VGG16	96.9%
Proposed	Proposed VGG16	97.00%

6. Conclusions

Building a reliable model is the primary goal for the classification of skin diseases in this research. This study presents two models based on CNNs and VGG16. With skin disease image datasets, multiple authors have attained accuracy levels of 94% to 95% by utilizing methodologies based on ML and DL. By 15 epoch, the suggested CNN model has obtained 96% and 100% of testing and training accuracy respectively. Similarly, by epoch 15, suggested VGG16 model has obtained 97% and 100% of testing and training accuracy respectively. When compared to alternative methods for skin disease categorization, where proposed VGG16 model achieved superior performance. The suggested model relies heavily on classification and real-time feature computation. Our suggested model is able to automatically extract features that categorize various skin conditions, according to the experimental results. A more reliable model for skin disease classification will be developed in the future by combining or hybridizing two or more methods. One potential drawback of the proposed model is that it may be more resource-intensive and computationally costly to train than other neural network types.

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