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Monkay Pox Skin Disease Detection Using Deep Learning

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Abstract

Human skin illnesses are widespread; millions of individuals are afflicted with different types of skin conditions. These illnesses often include unstated risks that increase the chance of developing skin cancer in addition to psychological sadness and low self-esteem. Because skin disease photos lack visual resolution, medical professionals and advanced equipment are required for the identification of these conditions. The suggested system makes use of preexisting models like Alex Net, ResNet, and InceptionV3 as well as deep learning methods like CNN architecture. A dataset of seven distinct illnesses has been collected in order to classify skin disorders. These include ailments such as nevus, seborrheic keratosis, melanoma, and so on. Images of burns and cuts, which were categorized as skin diseases by the majority of the systems in place, were included to the collection. Human labor is no longer required for tasks like manual feature extraction and data reconstruction for classification thanks to the use of deep learning algorithms.

1. INTRODUCTION

One of the most significant and rapidly growing bodily tissues is the skin. The term "burden of skin disease" refers to the multifaceted idea of the psychological, social, and economic effects of skin disease on individuals, their families, and society as a whole. This is a pollution that affects people of all ages. Because skin is such a delicate element of the body, it breaks easily. Over 3000 skin conditions exist. A sickness that degrades one's appearance will have a significant impact and may cause severe pain and permanent damage. Along with vitiligo, atopic eczema, psoriasis, and leg ulcers, the majority of chronic skin illnesses are not now fatal; instead, they may be identified as a complex issue that has implications for fitness that are social, psychological, and physical. However, skin cancers have the potential to be fatal, and their problem is related to how quickly they might develop. Skin disease is one of the most common illnesses among individuals worldwide. Examples of skin cancers (SCC) include melanoma, intraepithelial carcinoma, squamous cell carcinoma, and basal cell carcinoma (BCC). As of right now, skin cancer is more common than other newly discovered forms of breast and lung cancer [1].

Treatment for a number of skin conditions might be delayed because their symptoms can worsen for months before being identified. Consequently, computer-based illness diagnosis becomes relevant since it may provide a more accurate result faster than human analysis using laboratory processes. The most popular method for predicting skin diseases is deep learning. Even with modest computational models, deep learning models will uncover and investigate characteristics in unexposed data patterns using inferred data, leading to great efficiency. This work provides a reliable method for diagnosing skin conditions precisely while lowering diagnostic expenses using supervisory techniques. This has led the researchers to think of classifying the skin illness using a picture of the afflicted area and a deep learning algorithm. [2] The remainder of the article is structured as follows. Section 2 explores the relevant research on new skin disease detection methods in more detail. In Section 3, the suggested method of using deep learning algorithms to categorize the kind of skin ailment is covered. Section 4 presents the findings and discussion, while Section 5 concludes with recommendations for further research.

2. Related Work

It takes time to manually diagnose skin conditions by seeing and speaking with dermatologists. In most rural places, this is not an option. These rural folks must go to a neighboring city in order to get diagnosis and guidance. Much human labor is required for this. Not to add, seeing a doctor is an expensive affair. This also applies to interpersonal interaction, which is a needless bad in this pandemic emergency. Not all illnesses are communicable. Body contact occurs in the current system and cannot be avoided. According to current computer-aided diagnosis, burns and injuries are classified as skin conditions. These approaches' precision falls short of what is required. Therefore, the development of a computer-aided system that can identify skin disorders on its own and distinguish them from other skin concerns is necessary.

Quan Gan et al. [3] used texture features and picture color to identify skin diseases. The photos were pre-processed using median filtering. To get the picture segments, denoise images are rotated. After extracting text characteristics using the GLCM tool, psoriasis, dermatitis, and herpes were classified using support vector machines (SVM).

In their paper "Automatic Detection and Severity Measurement of Eczema Using Image Processing," Md Nafiul Alam et al. [4] proposed a computer algorithm and image processing-based model for automated eczema detection and severity measurement. By enabling patients to upload a photograph of the afflicted skin region, the system was able to identify and assess the severity of eczema. This method distinguished between moderate and severe eczema using statistical classification, feature extraction, and picture segmentation. Following the identification of the kind of eczema, an image's severity index was given.

Deep learning methods were used by researchers later on to categorize skin disorders. Long Short Term Memory and MobileNet V2, a deep learning-based system, were used by Parvathaneni Naga Srinivasu et al. [5] to categorize skin disorders. The rate of illness growth was estimated using a grey level co-occurrence matrix. The HAM10000 skin disease dataset yielded an accuracy of 85% for the algorithm. The CNN method was utilized by S. Malliga et al. [6] for training and categorizing a variety of clinical picture types. Three categories of skin conditions have been taken.

Melanoma, Nevus, and Seborrheic keratosis are the conditions that had a 71% accuracy rate.Using Alex NET, a pre-trained CNN model to extract the features, Nazia Hameed et al. [7] devised, implemented, and evaluated a method to categorize skin lesion images into one of five categories: healthy, acne, eczema, benign, or malignant melanoma. The total accuracy attained in the classification process using the SVM classifier is 86.21%.

3. Dataset

This research employed a dataset of seven skin diseases: Actinic Keratosis, Rosacea, Nevus, Bullous, Systemic Disease, Warts Mollusca, and Seborrheic Keratosis. There are over 7000 dermatoscopic pictures in this collection.

A total of seven hundred and fifty additional photos representing skin burns and cuts were added to the dataset. Skin wounds and burns have been classified as skin disorders under existing systems. In order to solve this issue, pictures of burns and cuts were gathered and included in the dataset. The data is divided into training data (5900) and validation data (1930) using a random (rand) algorithm.

4. Methodology

The suggested system is a web application that serves as a first stage in the diagnosis of a condition. A user uploads a photograph of the skin region that is afflicted, and the program determines the kind of sickness and provides some recommendations. The suggested architecture uses a deep learning-based approach to identify skin conditions. This system will analyze, process, and relegate the picture data based on different aspects of the photos by using computational approaches.Figure 1 below depicts the architecture of the system for detecting and classifying skin diseases.

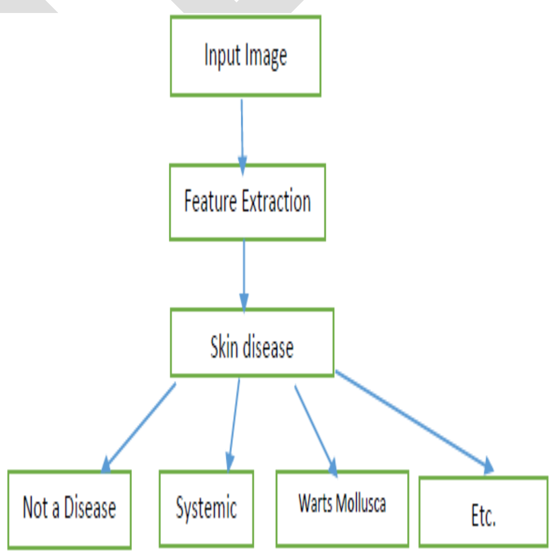

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Fig 1. Architecture of Detection and classification of Skin Diseases

4.1 Deep Neural Network Architectures

4.1.1 CNN architecture

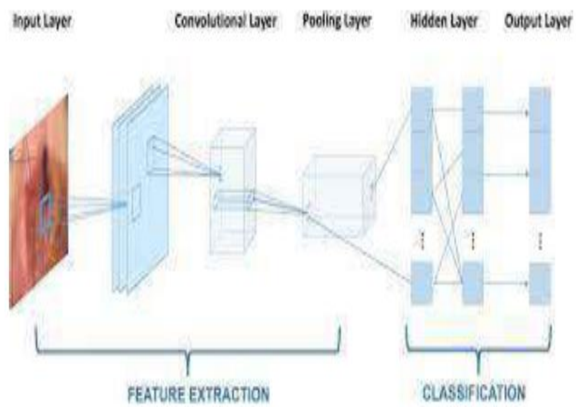

Fig 2. CNN Architecture

Figure 2 depicts a convolutional neural network with three layers: an input layer, hidden layers, and output layer. Middle layers in any feed-forward neural network are referred to be hidden since the activation function and final convolution hide their inputs and outputs. Convolution-performing layers are among the hidden layers of a convolutional neural network. Usually the Frobenius inner product, ReLU serves as this product's activation function. The convolution procedure creates a feature map as the convolution kernel moves along the layer's input matrix; this feature map then feeds into the input of the layer after it. Other layers including pooling layers, completely linked layers, and normalizing layers come after this. Convolutional layers send the result of their convolation of the input to the next layer. By merging the outputs of neuron clusters at one layer into a single neuron in the next layer, pooling layers minimize the dimensionality of data. Every neuron in one layer communicates with every other layer's neuron via fully linked layers [8].

4.1.2 ResNet152V2

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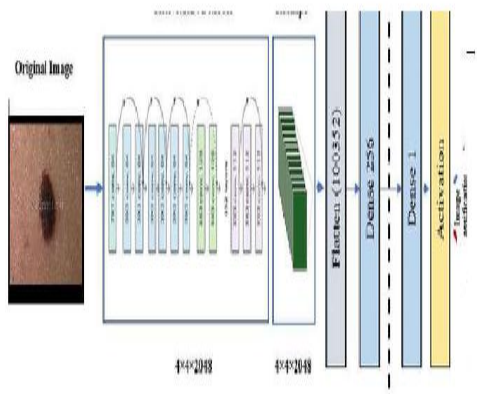

Fig.3 ResNet152V2 Architecture

Figure 3 displays the ResNet152V2 design. It uses the imageNet dataset to train a feature extraction model. Because the model is pre-trained, it may assist achieve acceptable accuracy more quickly than a conventional CNN. This is why the model contains starting weights. The ResNet152V2 model forms the basis of the model architecture, which is then followed by a flattening layer, a dropout layer, a dense layer with 128 neurons, a reshape layer, and a dense layer with Soft ax activation function to categorize the picture into the appropriate class. In order to slow down the deterioration of deep neural networks, Resnet incorporates a structure known as the residual learning unit [9]. The architecture of this unit is a feedforward network with a shortcut link that expands the network's capacity and produces additional outputs. This unit's primary advantage is that it improves classification accuracy without making the model more complicated.

4.1.3 AlexNet

Convolutional neural networks, such as the one known as AlexNet, have significantly influenced machine learning, particularly in the area of deep learning's application to machine vision. It is coupled with ReLU activations at each fully-connected and convolutional layer. Figure 4 illustrates the eight learnable parameter layers of the Alex net. The five layers of the model are composed of three completely linked layers that employ Relu activation after max pooling, with the exception of the output layer.

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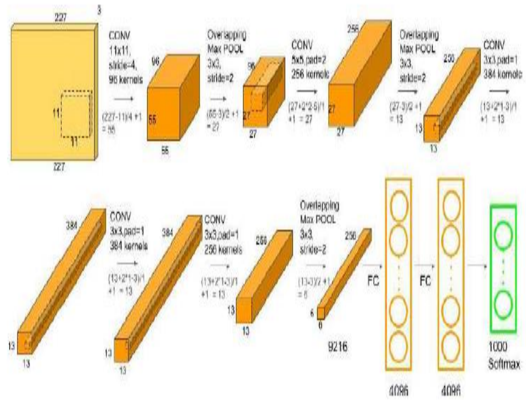

Fig. 4 Alex net Architecture

RGB pictures are the model's input. With the same precision, the speed is increased six times faster. Two Dropout layers were employed. Soft ax is the activation function that is used in the output layer. This design has 62.3 million parameters in total [10].

4.1.4 Inception-v3.

As seen in Figure 5, the Inception v3 retrained model was trained on the Image Net dataset, which comprises more than a million pictures across 1,000 classes on high-end computers. Retraining the last layer allows you to use the information that the model learnt during its first training to your smaller dataset, maintaining the accuracy of the classifications without requiring a lot of CPU resources or training [11].

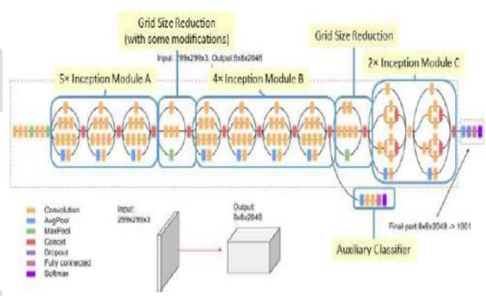

Fig.5. Inception-v3

5. Results and Discussions

Using deep learning methods, the proposed system would categorize the provided skin picture as either "Not a Skin disease" or one of the seven diseases—Warts Molluscum, Systemic illness, Seborrheic Keratosis, Nevus, Bullous, Actinic Keratosis, Acne, and Rosacea. The dataset is split

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into training and testing subsets, and CNN and three retrained networks—Alex Net, ResNet, and InceptionV3—are used to develop deep learning models. Table 1 displays the train and test accuracies of several models.

Table 1: Accuracy of Models in Training and Testing

Model	No. of epoch's	Training Accuracy	Test Accuracy
CNN	40	99	33.49
RESNET152V2	40	88.83	64.62
INCEPTION V3	45	65.46	61.23
ALEXNET	45	74.89	58.32

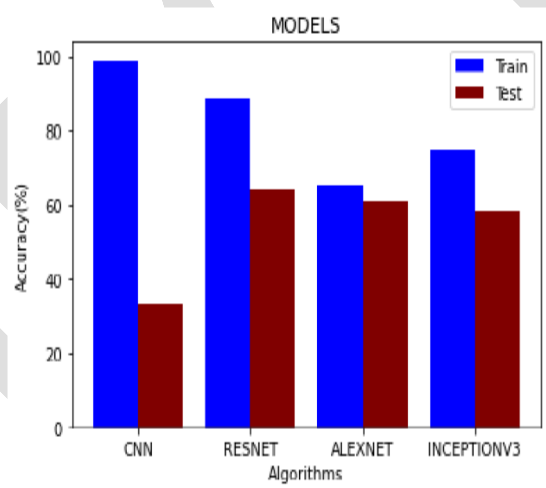

Fig.6 Performance of Deep neural networks

The bar graph (Fig.6) also displays the train and test accuracies of Inception-v3, CNN, Resnet, and Alexnet.The graph shows that CNN performed better on training data than it did on test data, which caused the model to become over fit. Test and Resnet Train accuracies are superior than those of the other models. Thus, skin disease detection and prediction may be achieved via the usage of Resnet architecture.

Fig. 7 displays a few of our experiment's findings. Our user interface allows you to enter a new picture. The system determines whether it is a skin condition or not. if the illness places it under one of the seven categories. identifies the skin area that is impacted and provides some advice for first care.

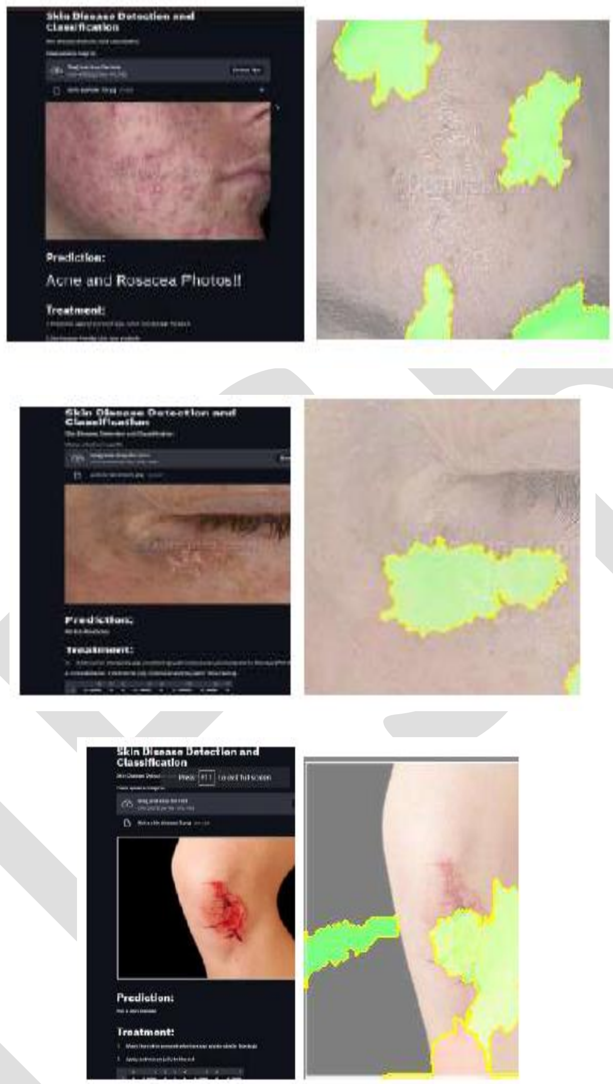

Fig.7 Diagnosis Results

6. CONCLUSION

Using CNN, Resnet, Alex net, and Inceptionv3, the viability of developing a global skin disease categorization system has been examined. With training data, CNN has done better than with testing data. Increasing the size of the training set and giving it greater variation will improve accuracy. Additionally, it has been shown that Resnet performs more accurately in the identification of skin conditions than other networks.

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