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DIAGNOSIS AND SEPARATION OF SKIN DISEASE IMAGES USING CONVOLUTIONAL NEURAL NETWORK AND VOTING METHOD

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ABSTRACT:

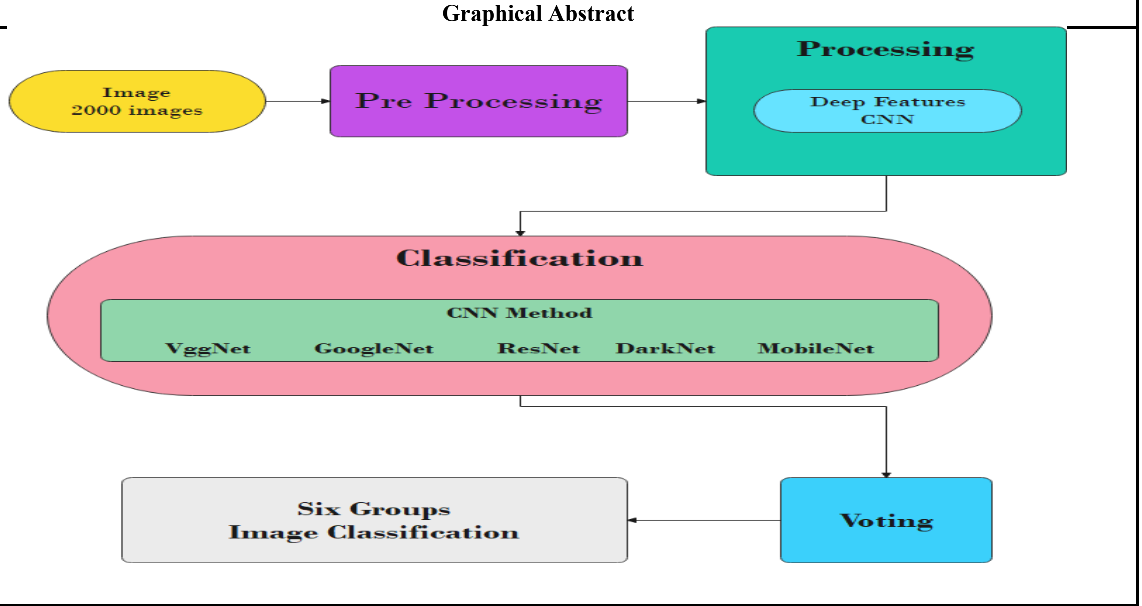
Misrecognition of skin images is a common occurrence worldwide. Misdiagnosis of skin diseases that are very similar causes many problems. Misdiagnosis has problems for doctors such as their similarities and complications. Diagnosis methods using convolutional neural network based on deep learning are getting much attention nowadays.

These methods have been able to show their ability to recognize and distinguish images well. Therefore, in this article, it has been tried to distinguish images with acceptable accuracy and high accuracy by using convolutional neural network based on deep learning.

In this article, first the deep features of the images were extracted using the convolutional neural network without manual intervention, and finally skin images with various architectures of convolutional networks including AlexNet, ResNet, VggNet, MobileNet, DarkNet and GoogleNet were checked, and the accuracy of the ResNet network was compared to other Architectures were distinguished with a higher accuracy of 99.1% and a sensitivity of 98.9%. In the final part, using the Voting method, the accuracy of the total result reached 99.93%. This study shows that the proposed method differentiates skin disease with acceptable accuracy.

Keywords: Convolutional Neural Network (CNN), skin images, deep learning, ResNet architecture, Voting

Graphical Abstract



1. INTRODUCTION

Human skin is the largest organ of the body and protects the body from fungal infections, allergies and viruses. The skin also controls body temperature.

There are about 3000 disorders in the world of dermatology. This large number includes many groups that have a wide spectrum. These diseases range from genetic disorders to infectious diseases, diseases caused by exposure to environmental factors, etc.

Most skin diseases are multifactorial. In general, it can be said that there are various reasons for the existence of a connection between the skin and the mind, that a skin disease can cause psychological problems in a person because of the unpleasant appearance it causes.

Accurate, timely and simple diagnosis of the images is very important and can speed up the treatment and recovery process. There are many diagnostic methods that convolutional neural networks have received much attention. Convolutional neural networks have been greatly appreciated by engineers and researchers due to their high ability to recognize images. Meanwhile, convolutional neural networks are very helpful to doctors and can simplify doctors' work.

In this article, an attempt has been made to recognize different types of images using convolutional neural networks.

The organization of the article is as follows. In the second part, the works related to the proposed method are presented, then in the third part, the proposed method is reported, and in the fourth part, the results of the proposed method are presented, and finally, in the fifth part, the obtained results are discussed and evaluated.

2. RELATED WORKS

Skin disease is one of the most common diseases among people all over the world. There are different types of skin diseases such as basal cell carcinoma (BCC), melanoma, intraepithelial carcinoma and squamous cell carcinoma (SCC) [1].

Skin diseases are one of the common diseases that about 10% of the world's people suffer from this disease [2]. These diseases have several factors that can be attributed to genetics and some environmental factors such as stress [3]. Factors causing and aggravating this disease can be

factors such as infections, mental factors, physical injuries, some drugs, hormonal and metabolic factors, sunlight. Studies conducted in England show that overweight men with this disease die on average 3.9 and 4.9 years earlier [4].
Often only experienced clinicians can achieve good diagnostic accuracy with these visual methods [5]. Histopathological examination of a suspicious lesion is the gold standard for the diagnosis of skin disease. Several examples of clinical images of common skin diseases are shown in Figure 1.

Figure 1. Examples of skin diseases

Therefore, the development of an effective method that can automatically distinguish different skin disease images would be simple as a very useful tool. Differentiation of a skin disease by dermoscopic images may be inaccurate or unreproducible because it depends on the experience of dermatologists. In practice, the diagnostic accuracy of melanoma from dermoscopic images by an inexperienced specialist is in the range of 0:75 to 0:84[5].
One of the limitations of diagnosis performed by human experts is that it is highly dependent on subjective judgment and varies greatly among different experts. In contrast, a computer-aided diagnostic (CAD) system is more targeted. By using manual features, traditional CAD systems for skin disease classification can achieve excellent performance in some skin disease diagnosis tasks [6]. The reason is that manual features are not suitable for universal diagnosis of skin disease. On the one hand, manual features are usually extracted specifically for a limited variety of skin diseases. They can hardly adapt to other types of skin diseases. On the other hand, due to the diversity of skin diseases, human-made features cannot be effective for every type of skin disease [6]. Generic valid features can be one of the solutions to this problem, which eliminates the need for feature engineering and extracts effective features automatically [7]. Many methods have been proposed for this task in the last few years [8]. However, most of them focused on dermoscopy or histopathology image processing tasks and mainly on mitosis and cancer marker detection[9]. Recently, deep learning methods have received much attention and have achieved excellent performance in various tasks such as image classification [10], image segmentation [11], object recognition [12], etc. Various researches [13] showed that deep learning methods are able to outperform humans in many computer vision tasks. One of the success factors of deep learning is its ability to learn semantic features automatically extracted from large data sets and used for classification and diagnosis[14].
In particular, a lot of work has been done on the use of deep learning methods in the diagnosis of skin diseases [15]. For example, [16] proposed a global skin disease classification system

based on a pre-trained convolutional neural network (CNN). The top classification accuracy was 80%, significantly better than the performance of human experts. Deep Neural Networks (DNNs) can deal with large variations in skin disease images by learning effective features with multiple layers. Despite these technological advances, the lack of large amounts of labeled clinical data has limited the widespread application of deep learning in skin disease diagnosis. During the last decade, many research articles, theses, and books have been published in the field of skin disease diagnosis [18]. In particular, there are several survey articles that have provided good reviews of methods used to diagnose skin diseases[19].
Many methods of convolutional neural network have attracted much attention from researchers, and easy access to implementation of deep learning algorithms, such as AlexNet, ResNet, VggNet, MobileNet, DarkNet, GoogleNet has accelerated the speed of applying deep learning for practical tasks.

3. MATERIALS METHOD

In this study, 2000 skin images from the DermNet NZ database were used. It was launched in 1996 by a team of dermatologists from New Zealand. It has become a world-renowned source of information on skin diseases. The images used in the online database are publicly available [28].

3-2- Deep features

Feature extraction from images is a very widely used and sensitive task for recognition and classification. The better this feature extraction is done, the better the recognition and separation will be. Here deep features are extracted from images using convolutional neural network.
Here, FC8 fully connected convolutional neural network is used to extract deep features. In this project, 1000 features are extracted and different images are recognized.

3-2-1- AlexNet architecture

Pre-trained deep convolutional neural networks for image classification won the ImageNet Large Scale Image Recognition Challenge 2012 (ILSVRC-2012). Although there are more network metrics that have appeared since then with many more layers, according to [26, 27] the network performs better.
This network has 8 layers, the first five layers are convolutional and the last three layers are fully connected. In between, there are layers called integration and activation. In this research, the AlexNet neural network with three fully connected layers is used, which you can see in Figure 2.

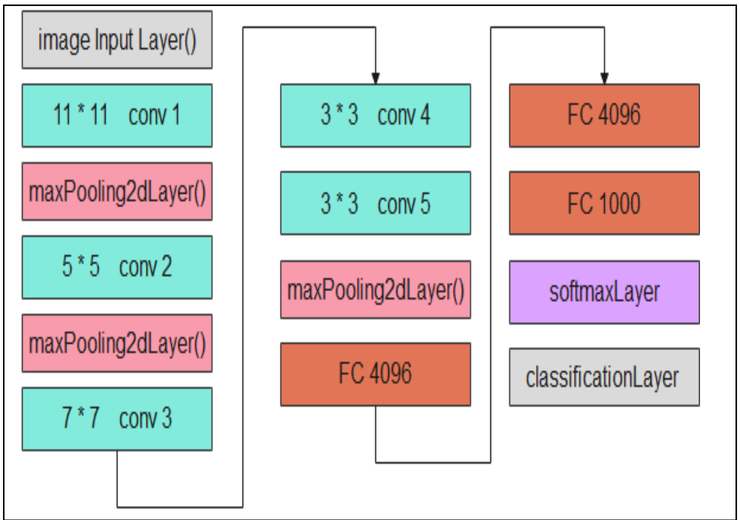


Figure 2. AlexNet convolution neural network image

3-2-2- ResNet architecture

In fact, ResNet was not a network that used shortcut connections, it introduced a gatewayed shortcut connection network. These parameterized gates control how much information is allowed to flow through the shortcut. Therefore, ResNet can be considered as a special case of deep network. You can see the ResNet network in Figure 3.

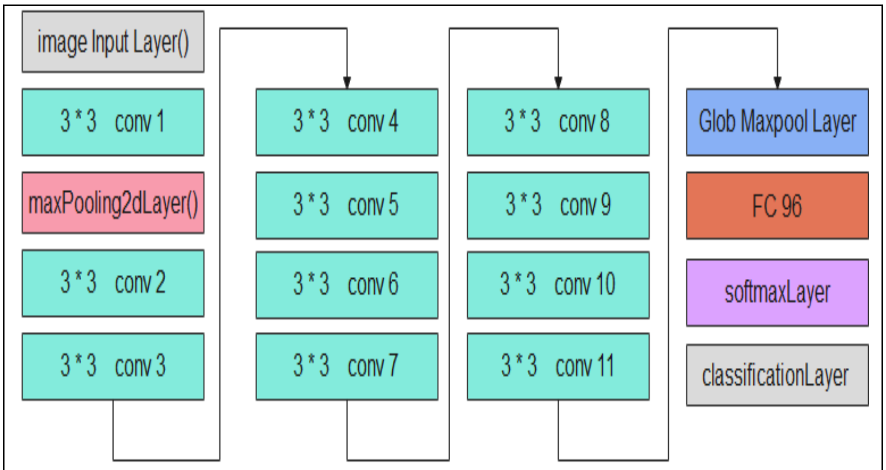


Figure 3. ResNet convolution neural network image

3-2-3- VggNet architecture

VGGNet is a convolutional neural network architecture proposed by Karen Simonian and Andrew Zisserman of Oxford University in 2014. The input of VGG-based convNet is a 224*224 RGB image. The preprocessing layer takes the RGB image with pixel values in the range 0 to 255 and subtracts the average image values calculated over the entire ImageNet training set.

The input images are passed through these weight layers after preprocessing. Training images are passed through a stack of convolutional layers. In the VGG16 architecture, there are a total of 13 convolution layers and 3 fully connected layers. Instead of having large filters, VGG has smaller filters (3x3) with greater depth. Finally, it has the same effective received field as if you had only one 7x7 convolutional layer. You can see the VggNet network architecture in Figure 4.

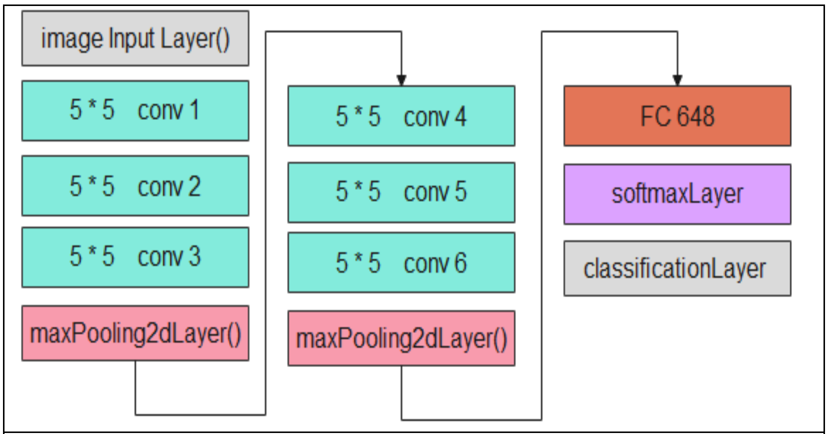


Figure 4. GoogleNet convolution neural network image

3-2-4- MobileNet

MobileNet is a convolutional neural network that is 53 layers deep. A network is pre-trained on over a million images.

The pre-trained network can classify images into 1000 object categories. As a result, the network has learned rich feature representation for a wide range of images. This grid has an image input size of 224 x 224.

You can see the MobileNet network in Figure 5.

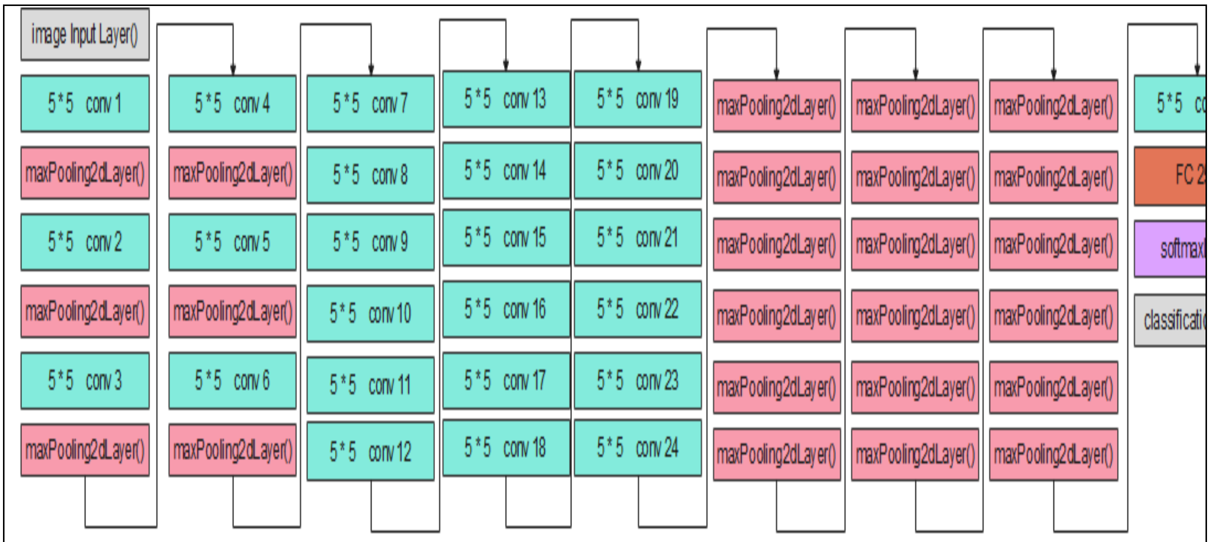


Figure 5. Image of MobileNet convolutional neural network

3-2-5- DarkNet

Darknet is an open source neural network framework and is a convolutional neural network that is 19 layers deep. A network is pre-trained on over a million images.

This network is able to classify 1000 groups. As a result, the network has learned rich feature representation for a wide range of images. This grid has an input image size of 256 x 256. You can see in figure 6.

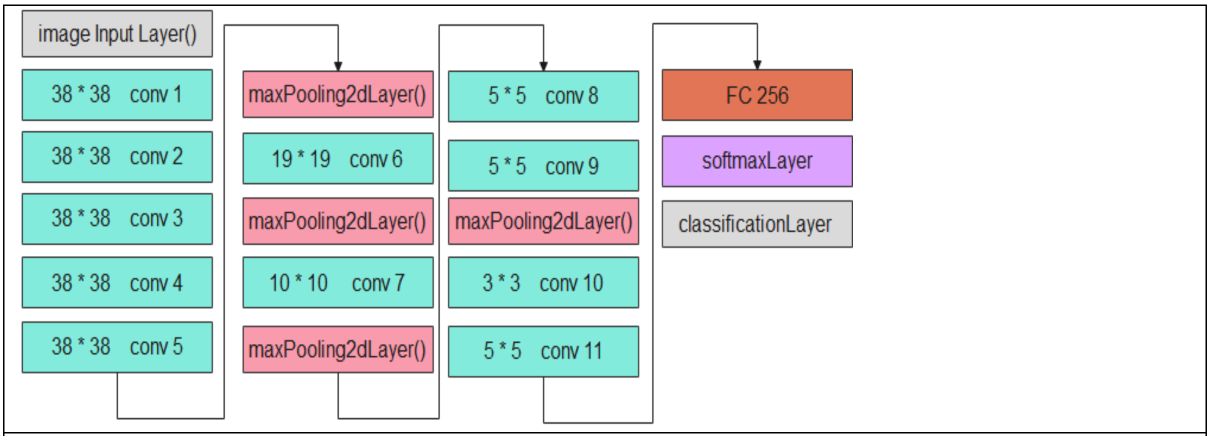


Figure 6. DarkNet convolutional neural network image

3-2-6- GoogleNet

Google Net was proposed by Google Research (in collaboration with various universities) in 2014 in a research paper titled "Going Deeper with Convolutions". This architecture won the 2014 ILSVRC Image Classification Challenge. It has a significant reduction in error rate compared to previous winners AlexNet (2012 ILSVRC winner) and ZF-Net (2013 ILSVRC winner) and a significantly lower error rate than VGG (2014 runner-up). This architecture uses techniques such as 1x1 convolution in the middle of the architecture and global average pooling.

GoogLeNet architecture is very different from previous architectures. It uses a variety of methods such as 1x1 convolution and global average pooling that allow it to create a deeper architecture.

The overall architecture is 22 layers deep. The architecture is designed with computational efficiency in mind. The idea behind this is that the architecture can be implemented on individual devices even with low computing resources. This architecture also includes two auxiliary classification layers that are connected to the output of Inception (4a) and Inception (4d) layers. You can see the Google Net architecture in Figure 7.

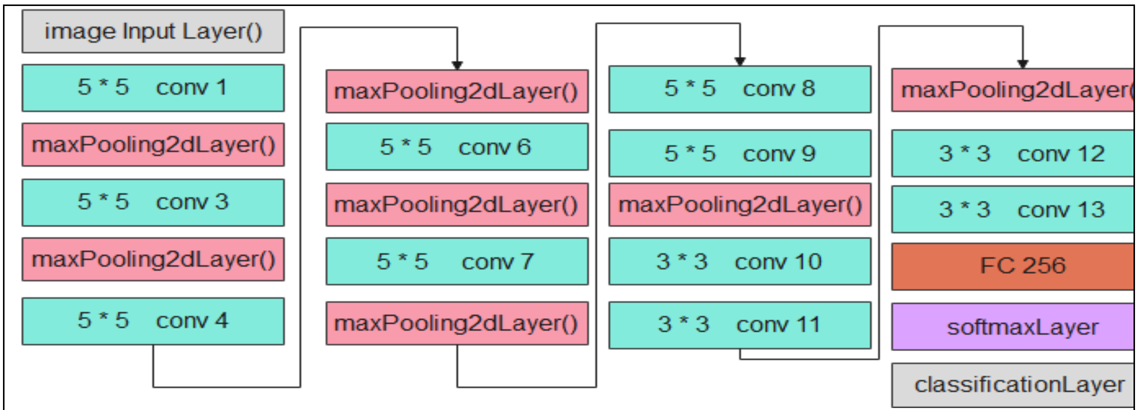


Figure 7. Image of GoogleNet convolutional neural network

4. RESULTS

In this study, 2000 images including 6 different groups were used. It is used in an online database [28] that is publicly available. You can see an example of images of skin diseases in Figure 1. Then the data of each image is converted to the required standard size of 227*227 and entered into 6 types of convolutional neural network architecture, including AlexNet, ResNet, VggNet, MobileNet, DarkNet, GoogleNet, and deep features are extracted without manual intervention. Then, using the convolutional neural network, two types of skin diseases were separated. To calculate accuracy and sensitivity, the confusion matrix according to equations 1 and 2 has been used. Equations 1 and 2 have been used according to the confusion matrix to calculate accuracy and sensitivity.

Equation 1

Accuracy = (TP + TN) / (TP + TN + FP + FN)	(1)

Equation 2

Sensitivity = (TP) /(TP + FN)	(2)

Table 1 shows the accuracy and sensitivity results of the classifiers.

TABLE 1. The results of all types of classifiers

Classifier	acc	sens
AlexNet	98.55	**97.78**
GoogleNet	97.45	**93.87**
DarkNet	98.1	**97.2**
MobileNet	97.21	**96.7**
ResNet	99.1	**98.9**
VggNet	96.72	**95.64**
Voting	99.93	**99.42**

4-1- Voting

In this part, out of the 5 results obtained from the classification of 5 groups, the group with the largest number was selected as the main selection and the overall result was reported based on the collective selection. According to the voting method, the accuracy increased significantly.

5- Discussion

The proposed method is shown in Figure 9.

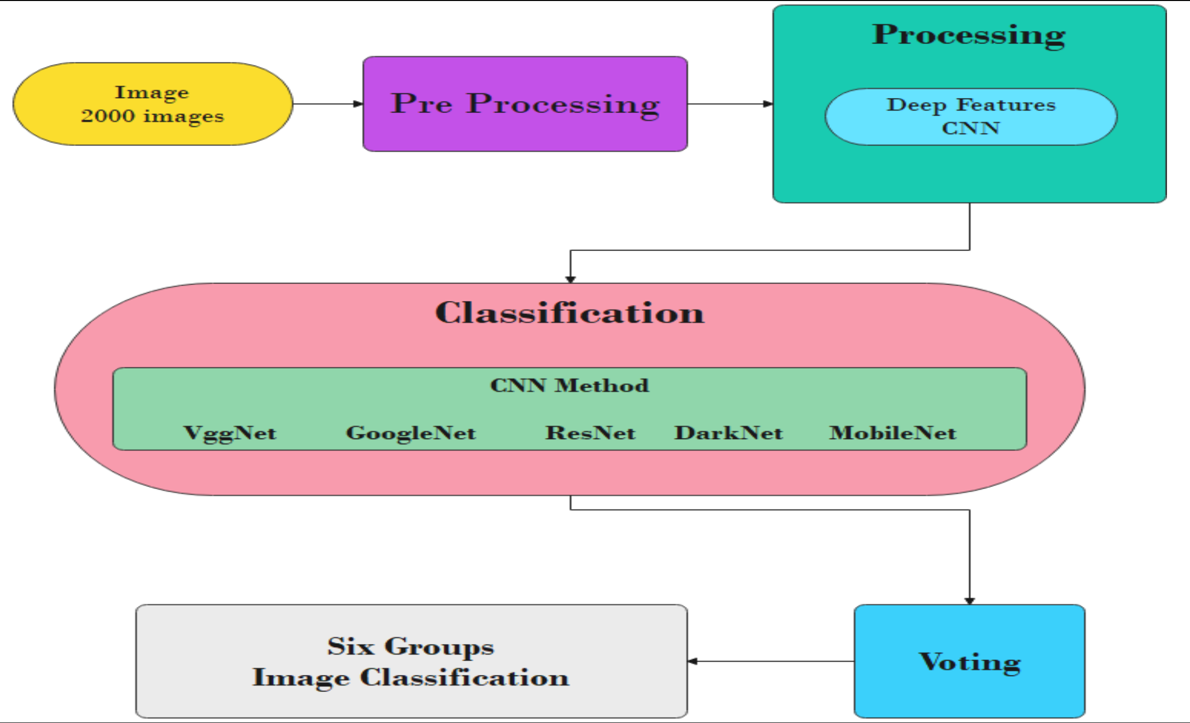


Figure 9. Flowchart of the proposed method

Table 2 shows the results and different algorithms in different datasets used.

TABLE 2. Results of other articles

Classifier	**Classifier**	**Classes**	**Ref**
AlexNet	NN	Skin diseases	**[6]**
GoogleNet	SVM	Eczema	**[9]**
DarkNet	CNN	5 groups image	**[10]**
MobileNet	CNN	psoriasis	**[29]**
ResNet	PSE-Net	psoriasis	**[30]**
VggNet	ResNet	6 groups image	**My method ResNet**
Voting	Voting	6 groups image	**My method Voting**

As you can see in Table 2, the accuracy of the proposed classifier is different from other classifiers. Is higher and is selected as the preferred classifier.

According to Table 2, it can be said that the proposed method has the following advantages.

We separated 6 groups of images of people with very similar skin diseases with high accuracy and sensitivity.

We used the features extracted from the image without manual intervention. And the system is fully automatic.

The main goal of this study is to provide a completely automated method without manual intervention based on deep learning to distinguish psoriasis from similar diseases. In this project, deep features are extracted from images without manual intervention. This reduces the need for humans and eliminates the need for human review of images. In this article, an attempt has been made to obtain a correct and reliable method to achieve the desired result.

As can be seen in Table 1, the classifier is more accurate than others, which helps us a lot in differentiation. According to the results and the method, it can be concluded that the proposed method is a safe and useful method for diagnosing skin diseases.

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