



Article Title: **Skin Disease Classification Using Deep Learning CNN**

Skin Disease Classification Using Deep Learning CNN

Greeshma P V Nair, Mrs. Jinitha A

¹Student, CSE department, Narayanaguru College of Engineering and Technology, Anna Unniversity.

²Professor, CSE department, Narayanaguru College of Engineering and Technology, Anna Unniversity.

ABSTRACT

Skin disease is one of the large numbers of spread diseases in the world. Its diagnoses are very difficult because of its difficulties in the skin texture, presence of hair on skin and colour. Thus, it is required to develop an efficient method for the diagnosis of skin disease based on deep learning in order to increase the accuracy of diagnosis for different skin types. Now a days, deep learning techniques are more popular in medical diagnosis system. This work focuses on skin disease prediction using deep learning technique. For the implementation, the dataset used for the skin disease prediction is the ISIC dataset with 9 category of skin diseases. For the classification, the deep learning algorithm used is Visual Geometry Group 19 (VGG 19). VGG 19 is a pretrained neural network, which can be used for the detection of skin disease detection using the concept of transfer learning. For that the neural network extracts image features from the skin images. The extracted features are used for the detection of skin disease within the 7 classes of skin diseases.

Keyword: Deep Learning, Transfer Learning, VGG 19.

1 Introduction

Skin is one in every of the most important and fastest growing tissues of the human body. Also, skin is a very sensitive part in the human body, thus the chances of getting diseased is of higher probability. Also, skin is regularly broken due to the fact it's far a touchy a part of the body. There are more than 3000 skin diseases exists. A cosmetically look spoiler disease will have a big effect and might reason extensive ache and everlasting injury. Most of the chronic skin conditions aren't right now deadly, they may be diagnosed as an extensive problem on fitness popularity which include physical, emotional and economic outcome. On the other hand, skin cancers are potentially lethal and their trouble is associated with the temporality that they carry. In the technical fields, machine learning is the application in every field and medical field diagnosis is the new technique added to it. Improvising machine learning based analytical tools are testing in improving and those are necessary to pick the right element and AI method to increase the accuracy. So, it is important to pick the right element and AI method to get more accuracy result. Machine-learning and image-processing dependent study and are applied in various areas such as fingerprint identification, face identification, tumour area recognition and for segmentation of effected area of skin disease. Deep learning algorithms are gaining prominence in skin disease classification. Skin diseases are quite



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difficult to identify and unpredictable because skin types are different for each person. These skin diseases are complex to diagnose and classify which type of disease it is. In many other countries it is too costly for people to consult a skin doctor. The mobiles in developing countries has becoming inexpensive diagnosis of skin diseases. The use of smart phones and camera technology and utilize of image processing technology of the devices for skin diagnosis. To develop a purpose, we have two phases to solve a problem. The implementation phase consists of deep learning classifier. It is difficult to diagnose the skin disease in the primary stage and other stages because of the change in the characteristic features of the skin such as colour and texture. This problem can be solving by using machine learning techniques on right selection of features to be determined for the analysis of skin disease samples. Deep learning is very effective tool for detecting and classifying the skin diseases. This tool is effective in verifying their results as it has pre-defined trained data set for classification. In this research, this system consists of 7 diseases, namely – melanoma, melanocytic nevi, benign keratosis-like lesions, basal cell carcinoma, pyogenic granulomas, actinic keratosis and dermatofibroma in this paper, multiple factors are studied for potential improvement in the classification accuracy of skin diseases using deep transfer learning. Here, VGG 19 is used to for classification via transfer learning. Transfer learning generally refers to a process where a model trained on one problem is used in some way on a second related problem. In deep learning, transfer learning is a technique whereby a neural network model is first trained on a problem similar to the problem that is being solved. One or more layers from the trained model are then used in a new model trained on the problem of interest.

2 Problem Statement

The pattern of skin diseases varies due to environmental factors, hygienic standards, social customs, and genetics. Several skin illnesses have symptoms that can take a long time to treat since they can grow for months before being recognized. As a result, computer-based disease diagnosis comes into play since it can produce a result in a short period of time with more accuracy than human analysis utilizing laboratory procedures. Deep Learning is the most widely used technology for skin disease prediction. Deep learning models will use inferred data to identify and explore features in unexposed data patterns, resulting in significant efficiency even with low computational models.

3 Proposed Work Explanation

The proposed system for skin disease classification using deep learning CNNs is based on the following steps:

Dataset collection: A dataset of skin lesion images is collected from publicly available sources or medical institutions. The dataset is annotated with labels indicating the disease category of each skin lesion image.

Data preprocessing: The skin lesion images are preprocessed by applying image augmentation techniques such as rotation, scaling, and flipping to increase the variability of the dataset. The images are also normalized to a standard size and color space.



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CNN architecture design: A CNN architecture is designed by choosing a pre-trained CNN such as VGG16 or ResNet as the feature extractor and adding fully connected layers for classification. The CNN architecture is trained using the skin lesion images and their corresponding labels.

Model evaluation: The performance of the CNN model is evaluated on a test set of skin lesion images using metrics such as accuracy, precision, recall, and F1-score.

Deployment: The trained CNN model is deployed as a web application or a mobile app that can take a skin lesion image as input and classify it into one of the disease categories. The proposed system aims to address the limitations of existing systems for skin disease classification by using state-of-the-art deep learning techniques for feature extraction and classification. The system's architecture is designed to improve the accuracy of classification while maintaining efficiency and scalability. The system's user interface is also designed to be user-friendly, enabling dermatologists and medical professionals to use the system without requiring extensive technical expertise. Overall, the proposed system has the potential to be a valuable tool for automating the diagnosis of skin diseases and improving the efficiency and accuracy of dermatological practices.



Figure 1: Proposed block diagram

3.1 Data Set

The HAM10000 dataset is a well-known dataset in the field of dermatology and machine learning. It contains images of various skin lesions, including melanoma, which is the deadliest form of skin cancer. The dataset consists of 10,015 dermoscopic images, which were collected from different patients. Each image is labelled with a unique identifier, as well as a clinical diagnosis provided by expert dermatologists. The dataset also includes additional metadata such as age, sex, and localization of the lesion. The HAM10000 dataset has been



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widely used for developing and evaluating machine learning algorithms for the diagnosis of skin cancer. It has been used for tasks such as image classification, where the goal is to classify images into different categories such as melanoma, benign nevi, and other types of skin lesions. By training on a large dataset like HAM10000, these models can learn to recognize patterns and features indicative of different skin conditions, including melanoma. Machine learning models can aid in the analysis process, but they should not be used as a substitute for medical expertise. The data set contains the following diseases: Apart from melanoma, the HAM10000 dataset includes images of other skin conditions such as melanocytic nevi, benign keratosis-like lesions, basal cell carcinoma, pyogenic granulomas, actinic keratosis and dermatofibroma.

3.2 Data Preprocessing

Data pre-processing is a process of preparing the raw data and making it suitable for building and training Machine Learning models. The aim of pre-processing is to improve the dataset for further processing. Pre-processing of data is carried out at the initial stage of the implementation of machine learning algorithm. The pre-processing task performed are reshaping and zooming.

3.3 Transfer Learning

Transfer learning is a machine learning technique where a model trained on one task is repurposed on a second related task. Transfer learning is an optimization that allows rapid progress or improved performance when modelling the second task. Transfer learning is related to problems such as multi-task learning and concept drift and is not exclusively an area of study for deep learning. Nevertheless, transfer learning is popular in deep learning given the enormous resources required to train deep learning models or the large and challenging datasets on which deep learning models are trained. In transfer learning, first train a base network on a base dataset and task, and then we repurpose the learned features, or transfer them, to a second target network to be trained on a target dataset and task. This process will tend to work if the features are general, meaning suitable to both base and target tasks, instead of specific to the base task. This form of transfer learning used in deep learning is called inductive transfer. This is where the scope of possible models (model bias) is narrowed in a beneficial way by using a model fit on a different but related task.

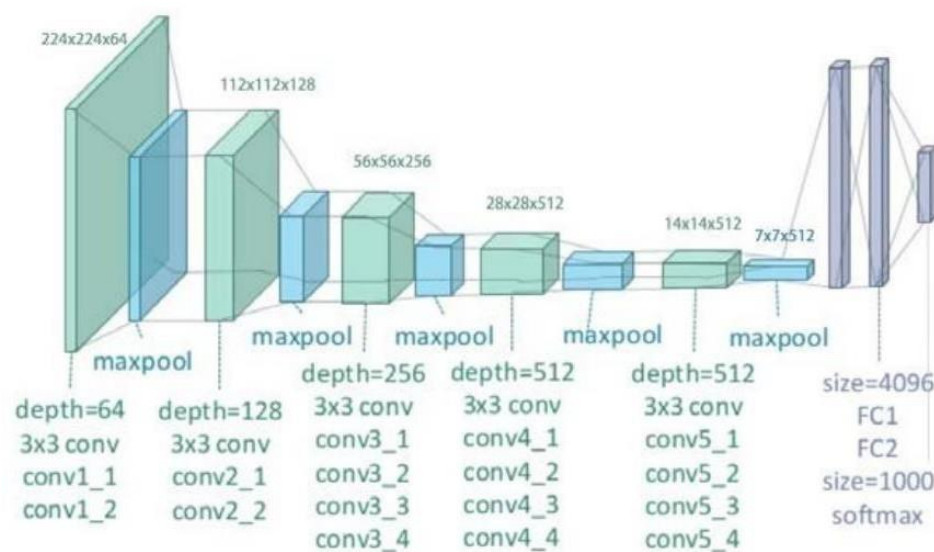
3.4 Classification Using Vgg 19 (Transfer Learning)

VGG-19 refers to the 19-layer variant of the VGG (Visual Geometry Group) convolutional neural network architecture. It was introduced by the Visual Geometry Group at the University of Oxford in 2014. VGG-19 gained popularity and served as a foundation for many subsequent deep learning models. The VGG-19 architecture is composed of 19 layers, including 16 convolutional layers and 3 fully connected layers. The convolutional layers are



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designed to extract hierarchical features from input images, while the fully connected layers at the end of the network help in making predictions based on those features. The key characteristic of the VGG-19 architecture is its use of small 3x3 convolutional filters throughout the network, with max pooling layers in between. The small filter size allows the network to capture more fine-grained details, while the pooling layers help in reducing the spatial dimensions and extracting the most salient features.



The VGG-19 architecture:

- Input image (typically 224x224 pixels).
- Convolutional layers with 64 filters of size 3x3, followed by a ReLU activation function.
- Max pooling layer with 2x2 window and stride of 2.
- Convolutional layers with 128 filters of size 3x3, followed by a ReLU activation function.
- Max pooling layer with 2x2 window and stride of 2.
- Convolutional layers with 256 filters of size 3x3, followed by a ReLU activation function.
- Convolutional layers with 256 filters of size 3x3, followed by a ReLU activation function.
- Max pooling layer with 2x2 window and stride of 2.
- Convolutional layers with 512 filters of size 3x3, followed by a ReLU activation function.
- Convolutional layers with 512 filters of size 3x3, followed by a ReLU activation function.
- Max pooling layer with 2x2 window and stride of 2.



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- Convolutional layers with 512 filters of size 3x3, followed by a ReLU activation function.
- Convolutional layers with 512 filters of size 3x3, followed by a ReLU activation function.
- Max pooling layer with 2x2 window and stride of 2.
- Fully connected layer with 4096 units and a ReLU activation function.
- Fully connected layer with 4096 units and a ReLU activation function.
- Fully connected layer with 1000 units (output classes), followed by a softmax activation function.

4 Detailed Description

Input: The input to the VGG-19 network is an RGB image typically with a size of 224x224 pixels.

Convolutional Layers: The network begins with a series of convolutional layers. VGG-19 has a total of 16 convolutional layers. Each convolutional layer uses a 3x3 filter and applies a set of learned weights to the input image to extract features. The output of each convolutional layer is passed through a Rectified Linear Unit (ReLU) activation function, which introduces non-linearity into the network.

Max Pooling Layers: After each set of convolutional layers (two consecutive convolutional layers), a max pooling layer is applied. The max pooling layer reduces the spatial dimensions of the feature maps while retaining the most salient information. It operates on a 2x2 window with a stride of 2, effectively halving the size of the feature maps.

Fully Connected Layers: After the convolutional and pooling layers, three fully connected layers are added to the network. These layers serve as classifiers based on the extracted features. The first two fully connected layers have 4096 units each, and the third fully connected layer has 1000 units (corresponding to the number of classes in the ImageNet dataset). ReLU activation is applied to each of these layers as well.

Softmax Layer: The output of the last fully connected layer is passed through a softmax activation function, which converts the raw class scores into probabilities. Each probability represents the likelihood of the input image belonging to a specific class.

Training: VGG-19 was initially trained on the ImageNet dataset, which contains millions of labeled images spanning 1000 different classes. During training, the network learns the optimal weights for the convolutional and fully connected layers by minimizing a predefined loss function, such as cross-entropy loss. This process is typically performed using gradient-based optimization algorithms like stochastic gradient descent (SGD).

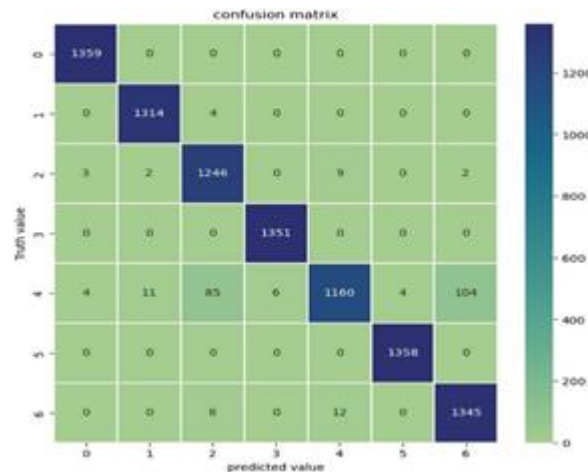
Transfer Learning and Fine-tuning: One significant advantage of VGG-19 and similar architectures is their ability to be used for transfer learning. By utilizing pre-trained models.



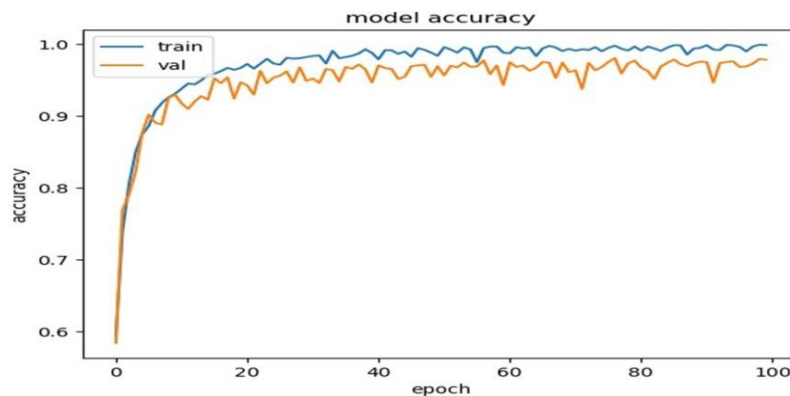
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On large-scale datasets like ImageNet, the learned features can be transferred to other tasks or datasets with limited labeled data. The pre-trained weights can be fine-tuned on the target dataset by retraining the fully connected layers while keeping the convolutional layers frozen or fine-tuning them to adapt to the specific task. Overall, VGG-19 is a deep convolutional neural network architecture that has made significant contributions to the field of computer vision. Its simplicity and effectiveness have led to its widespread adoption as a baseline architecture for various vision tasks and as a starting point for developing more advanced models.

5 Results and Discussion



The figure, shows the confusion matrix generated when evaluating VGG19. Confusion matrix is generated using the confusion_matrix () method of sklearn python library. And it is visualized as a heat map using python visualization method named, matplotlib and sea born. The values in the confusion matrix represents the number of correct predictions and number of wrong predictions of CNN model. In the confusion matrix, the diagonal value represents the number of correct predictions of CNN model and the non-diagonal element represents the number of wrong predictions. In the figure, it is clear that number of correct predictions is higher and number of wrong predictions is low.

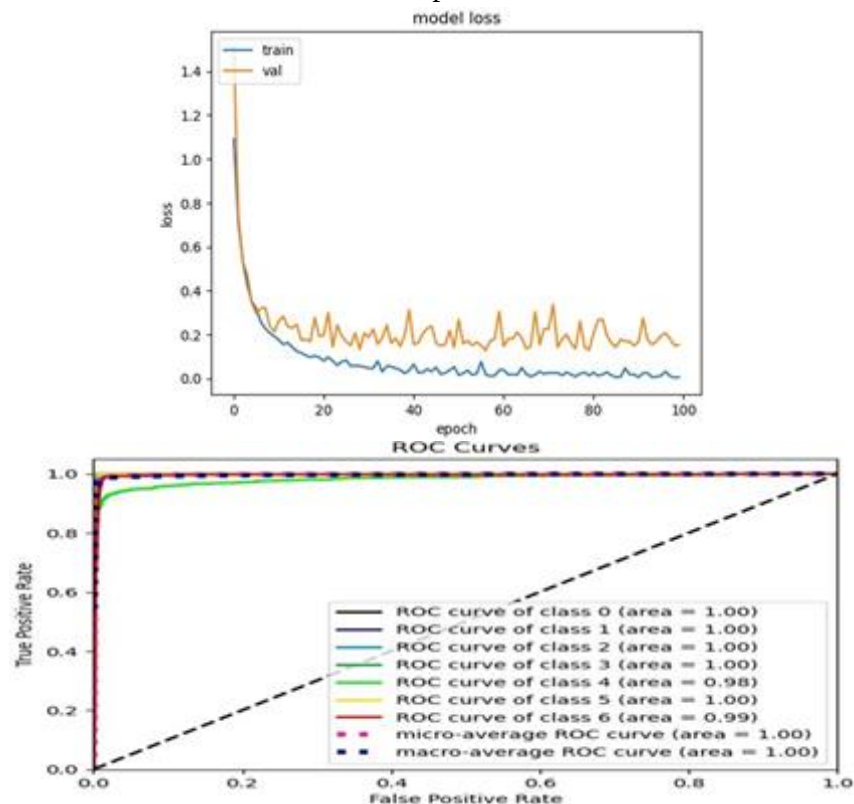


In this figure, the x-axis represents the number of training samples, while the y-axis



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represents the accuracy of the model on the validation set. As more training samples are used, the model's accuracy gradually increases. Initially, with a small number of samples, the model may have a lower accuracy due to limited information. However, as more data is provided, the model learns and its accuracy improves. Eventually, there may be a plateau where adding more training samples does not significantly impact the model's accuracy. In this figure, the x-axis represents the number of training iterations or epochs, while the y-axis represents the loss value. As the model is trained, the loss generally decreases, indicating that the model is improving its predictive capabilities. Initially, the loss may be high as the model starts with random or uninitialized weights. However, as the training progresses, the loss decreases, and the model learns to make better predictions.



The ROC curve is often used in conjunction with the Area under the Curve (AUC) metric. The AUC represents the overall performance of the model and is a measure of the curve's area. A perfect classifier would have an AUC score of 1, while a random classifier would have an AUC score of 0.5. The ROC curve provides a visual representation of the model's performance across different thresholds and helps in evaluating the model's ability to discriminate between positive and negative instances. It allows you to select an appropriate threshold based on the desired balance between TPR and FPR for your specific problem and application.



6 Conclusion

In this work, deep learning algorithm is used to detect nine types of skin diseases. Skin Disease detection is important due to the severity in the disease. Dermatological process to detect skin disease type is very costly compare to the proposed work. In this work, use VGG 19. No need of manual feature extraction from input image, since, deep learning networks extracts features automatically. The training image is fed into the VGG 19 network for training. After training completed the network is capable of detecting 7 types of skin diseases from input skin images.

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