18CSE353T – Digital Image Processing

Mini Project

Project Title:

Implementing Image Processing Techniques and Machine Learning Algorithms for Dermatology Disease Detection and Classification

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Literature Survey

Skin diseases are more common than other diseases. Skin diseases may be caused by fungal infection, bacteria, allergy, or viruses, etc. The advancement of lasers and Photonics based medical technology has made it possible to diagnose the skin diseases much more quickly and accurately. But the cost of such diagnosis is still limited and very expensive. So, image processing techniques help to build automated screening system for dermatology at an initial stage. The extraction of features plays a key role in helping to classify skin diseases. Computer vision has a role in the detection of skin diseases in a variety of techniques. This [1] work contributes in the research of skin disease detection. They propose an image processing-based method to detect skin diseases. This method takes the digital image of disease effect skin area, then use image analysis to identify the type of disease. The approach works on the inputs of a color image. Then resize the of the image to extract features using pre trained convolutional neural network. After that classified feature using Multiclass SVM. Finally, the results are shown to the user, including the type of disease, spread, and severity. The system successfully detects 3 different types of skin diseases with an accuracy rate of 100%.

[2] Convolutional neural networks (CNNs) have shown great power for the analysis of clinical images, and an increasing number of studies have reported promising results for CNNs in a variety of diseases. Here,[2] report their development of a smartphone-based platform to assist the Pso, Ecz and AD diagnosis.[2] use five-fold cross-validation to validate the effectiveness of our algorithm. In each fold, the validation set is a randomly chosen subset that contains around 20% of the cases. In this study, it is demonstrated that deep learning can be effectively applied in dermatology outside of melanoma diagnosis.

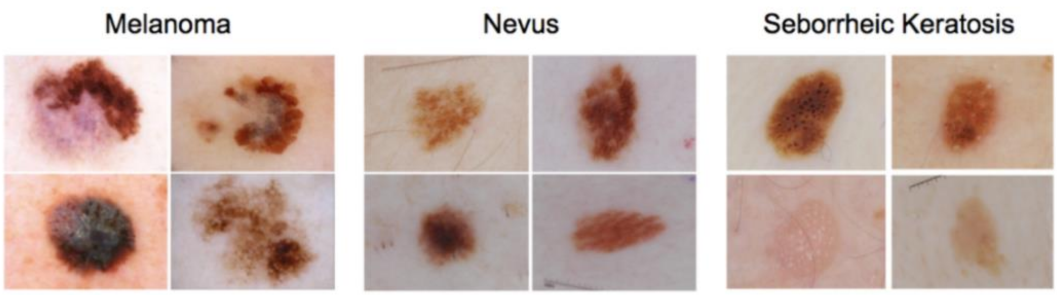
[3] develops a convolutional neural network model to classify clinically relevant selected multiple-lesion skin diseases, this in accordance to the STARD guidelines. This was an image-based retrospective study using multi-task learning for binary classification. A VGG-16 model was trained on 16,543 non-standardized images. Image data was distributed in training set (80%), validation set (10%), and test set (10%). All images were collected from a clinical database of a Danish population attending one dermatological department. Included were patients categorized with ICD-10 codes related to acne, rosacea, psoriasis, eczema, and cutaneous t-cell lymphoma. The performance rates reported were equal or superior to those reported for general practitioners with dermatological training, indicating that computer-aided diagnostic models based on convolutional neural network may potentially be employed for diagnosing multiple-lesion skin diseases.

[4] a method based on vertical image segmentation, GLCM, and SVM is proposed to identify three various types of skin diseases, namely, herpes, paederus dermatitis, and psoriasis. Firstly, the sample images of three skin diseases need to be preprocessed. Secondly, the vertical image is segmented and made corresponding geometric transformation. Based on this, three types of skin diseases' features are extracted, and their correlated parameters of feature texture and pixels of lesion areas are collected through image segmentation. Finally, the symptoms of herpes, paederus dermatitis, and

psoriasis are identified by utilizing the support vector machine (SVM) method in order to improve identification accuracy.

The above literature has made significant achievements on the identification of skin diseases.

Feature Selection



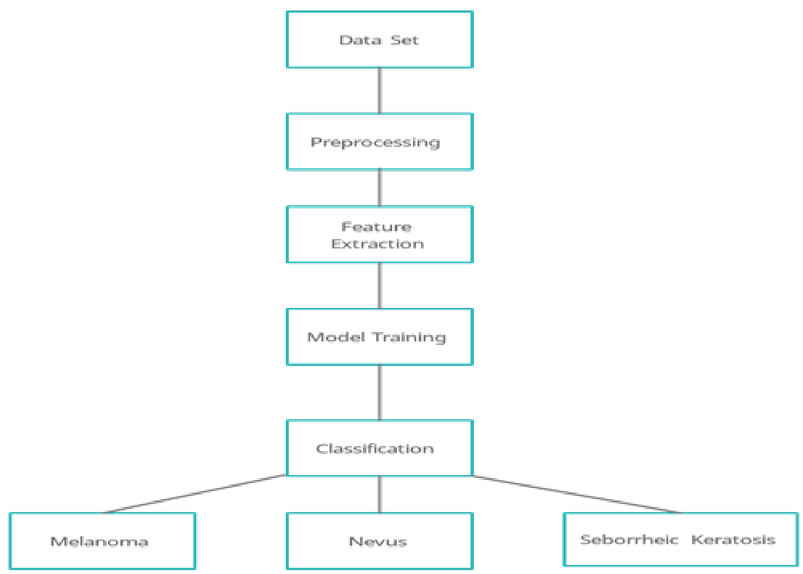
Based on the segmentation results, hand-crafted features can be extracted for melanoma recognition. Celebi et al. extracted several features including color and texture from segmented lesion region for skin lesion classification [5]. Schaefer used an automatic border detection approach [6] to segment the lesion area and then ensemble the extracted features, i.e., shape, texture and color, for melanoma recognition [7]. On the other hand, some investigations [8-10] attempted to directly employ hand-crafted features for melanoma recognition without segmentation steps. Different from approaches using hand-crafted features, deep learning networks use hierarchical structure to automatically extract features. Due to the breakthroughs made by deep learning in increasing the number of medical image processing tasks, some research started to apply a deep learning approach for melanoma recognition.

In our model we have used CNN model to classify the images into three categories that are- Melanoma, Nevus, Seborrheic Keratosis.

Training of Algorithm

1.Methodology

In this section, the methodology of the proposed system for detection, extraction and classification of skin diseases images is described. The system will help significantly in the detection of melanoma, nevus and seborrheic keratosis. The whole architecture can be divided into several modules consisting of pre-processing, feature extraction, and classification. The block diagram of the system is shown below:



2.Pre-processing:

All the images are subjected to various types of pre-processing techniques followed by feature extraction.

Firstly, the images need to be converted to gray scale images as luminance is the required part that represents all the features present in the image. Next step applied is a sharpening filter function to the images to increase the contrast of the image.

To resolve the problem of different image sizes in the database an input image is either increased or decreased in size. Unifying the image size will get the same number of features from all images. Moreover, resizing the image reduces processing time and thus increases system performance.

Let’s say the original image is of size 260×325 pixels. After pre-processing the resized image will be of the size of 224×224 pixels.

3.Feature Extraction:

At the beginning, Convolutional Neural Network (CNN) is a set of stacked layers involving only the linear process. These layers are learned in a joint manner. The main building blocks of any CNN model are: convolutional layer, pooling layer, nonlinear Rectified Linear Units (ReLU) layer connected to a regular multilayer neural network called fully connected layer, and a loss layer at the backend. CNN has known for its significant performance in applications as the visual tasks and natural language processing.

The block diagram of the model is shown below:

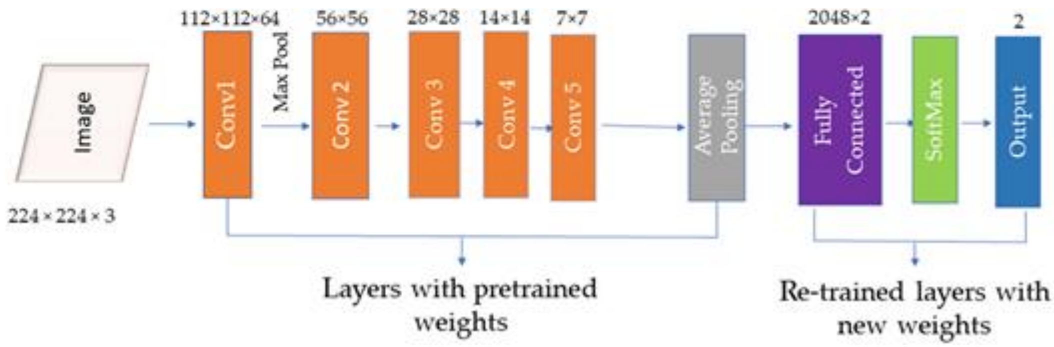


Fig. above represent - The customized ResNet50 architecture deployed in the proposed classification task.

4. Model Training

ResNet-50 is a convolutional neural network that is 50 layers deep. We can load a pre trained version of the network trained on more than a million images.

The pretrained network can classify images into 1000 object categories.

We have used about 1400 images with 3 types of categories of skin diseases as discussed above for training and testing purposes.

To detect the behavior, events are transformed into a visual representation in the time-frequency domain (a scalogram), deep features are extracted using the pretrained convolutional neural network (CNN) ResNet-50, and then the images are classified using a Support Vector Machine (SVM) algorithm. We proposed feature extraction from a pretrained convolutional neural network because it is the easiest and robust approach to use the power of pretrained deep learning networks.

The main purpose of using Resnet50 + SVM is that it has better accuracy rate as compared to other models like GLCM + SVM, Squeezenet, AlexNet etc.

5.Classification:

Classification is a computer vision method. After extracting features, the role of classification is to classify the image via Support Vector Machine (SVM). A SVM can train classifier using extracted features from the training set.

The input images are pre-processed, then features are extracted using pretrained CNN. Finally, classification is performed using SVM classifier.

Evaluation of Trained Algorithm

```
confMat =

   154    56    59
    14   198    57
    21    47   201
```

Confusion matrix for the trained model for the classes Melanoma, Nevus, Seborrheic Keratosis.

Accuracy= (154+198+201) / (154+198+201+56+59+14+57+21+47) =553/553+254

Accuracy=0.68525402726= **68.52%**

Critical Review and Summary of the Achieved Results

The goal of this application is to develop a system which recognizes skin diseases and displays results to the user as detected disease, for that user have to upload an image then, Image dispensation starts with the digitized color image of the diseased part. Finally, by smearing the CNN, skin disease can be forecast. The dataset covers types of diseased skin images. The training dataset trains the data whereas the testing dataset matches the images. The accuracy of training is 70% whereas the accuracy of testing is 68.52%.

A System has been successfully implemented for the identification of correct skin disease; the correct classification algorithm must be chosen. Result accuracy will increase with image quality, and feature combinations. In this study, we compared two features for identification of disease. they are color, texture. and they classify in three different combinations. We obtained the following result using CNN. In future, classification algorithms can be tested with different image quality, quantity and features to achieve better identification of disease.

Reference

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