Virtual Dermoscopy Using Deep Learning Approach

Debabrata Swain, Sanket Bijawe, Prasanna Akolkar, Mihir Mahajani, Aditya Shinde, and Pradunya Maladhari

Abstract Dermoscopy is one of the most irregular and challenging areas to diagnose as it is very complex. In the sphere of dermatology, numerous numbers of times, thorough examinations are required to be carried out to resolve upon the skin ailment the patient may be facing. Different practitioners may take a different amount of time to detect the skin disease. So, a system is required that can efficiently and accurately diagnose the skin conditions without any such restrictions. This paper presents an automated dermatological diagnostic system using a deep learning approach. Dermatology is the branch of medicine which deals with the identification and treatment of skin diseases. The presented system is a machine interference in contradiction to the traditional medical personnel-based belief of dermatological diagnosis. The entire system works on the two mutually dependent steps. The first is preprocessing of image of that part of skin that is infected and the second step is used to recognize the disease. The system uses convolutional neural networks and feedforward backpropagation for the identification of skin disease. The system gives an accuracy of 93.063% while testing on a total of 180 image samples for six disease classes.

Keywords Automated · Backpropagation · Classification · Dermatology · Diagnostic · Feedforward

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1 Introduction

Some of the most widespread diseases across the globe are dermatological diseases. In spite of being so common, their detection is very confusing and needs thorough expertise in that field. It is estimated that more than 9500 people in the United States are diagnosed with skin cancer every day. There is irregular schooling in dermatology at the college level, which shows that the trainees should consider reevaluating their existing skills. Right now, about 90% of skin diseases are being managed only by using primary care. These imply that if we take care at an early stage, most of the skin disease dilemmas could be resolved. Skin diseases can have a significant impact on the quality of life of patients. The number of skin diseases are increasing constantly and results obtained are dependent on the initial diagnosis. Some people cannot afford to go to a dermatologist for their skin problems. In the countries that are not technologically forward, there have been numerous attempts to implement traditional medicine. But the attempts have met with some problems such as the shortage of medical expertise and a very high cost of medical tools. Skin diseases are a result of environmental factors as well as various other causes. The important tools that are necessary for the timely detection of such diseases are not very easily available to a large percentage of the population worldwide, which is one of the major reasons for a very high mortality rate in these cases. This paper provides a method to detect some of the types of skin diseases. This project aims to collect skin disease image data, preprocesses that data and creates an intelligent prediction system for better identification of skin diseases. The image of the affected skin part is provided by the user as an input to the system, which then performs processing on it by extracting features using the Convolutional Neural Networks algorithm. To diagnose skin diseases, it uses a SoftMax image classifier. The proposed system will thus be very useful for those places which have a very limited access to medical facilities. It can also be a very handy tool for the doctors to verify their diagnosis in case of those diseases which cannot be detected accurately in their initial stages, like melanoma. Thus, this paper proposes skin disease identification and classification method based on Convolutional Neural Network. In our system, we have worked on classifying 6 different skin ailments listed as Acne and Rosacea, Bullous Disease, Cellulitis Impetigo and other Bacterial Infections, Eczema, Melanoma Skin Cancer Nevi, and Nail Fungus. We have made use of Image Processing and Artificial Neural Networks to classify the different types of skin diseases. To convert an input image to an output label we are using a convolutional neural network. It is particularly designed for image data processing. In this paper, we will be discussing the architecture, methodology and pre-processing algorithms used in our system.

2 Background

2.1 A Brief Overview on Related Works

Rathod et al. [1] proposed a method for detecting various kinds of skin diseases. CNN algorithm was used for feature extraction along with an image classifier as SoftMax to diagnose diseases. Initially, an accuracy of about 70% was achieved. Their accuracy was then increased by increasing the training data. Further accuracy of 90% was achieved on 6 diseases. Yasir et al. [2] used computer vision along with image processing and fed the data to artificial neural networks. This system, when tested on a dataset of 775 images of 9 different disease types, it gave an accuracy of 90%. Asghar et al. [3] proposed a rule-based expert system was developed. This system used forward chaining along with a depth-first search to detect diseases. The paper by Amarathunga [4] gave an approach which could diagnose the skin disease as well as give medical treatment or advice quickly. That system used image processing as well as data mining. To enhance the image, different preprocessing techniques were used. Finally, the use of data mining techniques for suggestions of treatment and advice provided them with accuracies of 85%, 95% and 85% for Eczema, Impetigo, and Melanoma respectively. In another paper published by Liao et al. [5] a universal skin disease detection system was constructed using CNN. They got datasets from Dermnet and OLE. They had 73.1% Top-1 accuracy and 91.0% Top-5 accuracy on Dermnet and 31.1% Top-1 and 69.5% Top-5 accuracy on OLE. Lopez et al. [6] used VGGNet convolutional neural network architecture along with the transfer learning paradigm. They achieved a sensitivity value of 78.66% as well as 79.74% precision while working on ISIC Archive dataset.

2.2 Database Description

Tons of data surrounds us today, generated from various instances by various sources. Each data generated belongs to different and heterogeneous formats, each of several different domains. This collected data can prove to be immensely valuable if used properly. There are various approaches to obtain live data for research and development. The skin disease database used is scraped from "Dermnet"—a web portal that contains a total of 23,000 images which is further classified in 46 diseases. Our scraped database contains 6 diseases which are a total of 1600 images. Figure 1 flow diagram describes our approach towards dataset scraping. All the labels of the scrapped disease are listed as follows:

1. Acne-and-Rosacea-Photos
2. Bullous-Disease-Photos
3. Cellulitis-Impetigo-and-other-Bacterial-Infections
4. Eczema-Photos

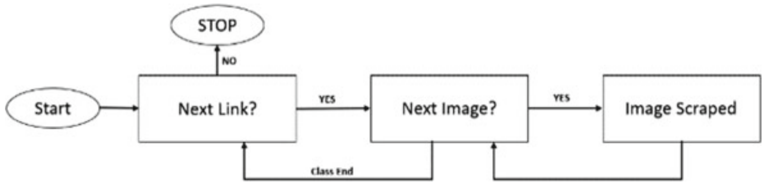

Fig. 1 Flow diagram for dataset scraping

5. Melanoma-Skin-Cancer-Nevi-and-Moles
6. Nail-Fungus-and-other-Nail-Disease.

3 The Proposed Methodology and Implementation

3.1 Brief Overview of System

The proposed methodology, depicted in Fig. 2, is based on two primary parts, Image pre-processing unit and a classifier unit. The image processor unit will augment the sample/image by reshaping it and then the image will be divided into segments. Then the image will be sent to the convolutional classifier for feature extraction and further classification.

- **Image Processing Unit**: This unit focuses on the affected part by converting the image into the RGB form. Feature extraction is a major step in the classification problem as it is the core of the image classification problem. So, both the training and testing images are resized into proper format before sending it to the classifier unit. Furthermore, all the training images are passed through the rotational and

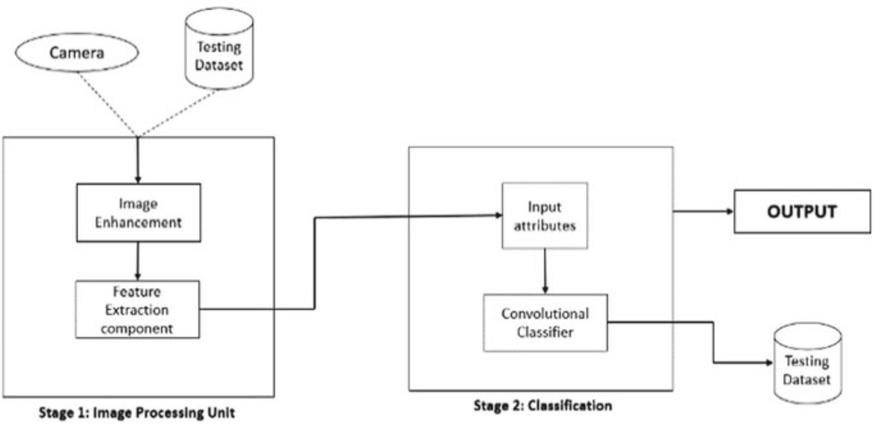

Fig. 2 Architecture of proposed model

positional variant i.e. they are shifted vertically or horizontally, rotated clockwise or anti-clockwise by 10% or scaled in/out, thus sustaining the process of efficiently training the model [7].

- **Classification Unit**: This unit classifies the images into pre-defined classes using a convolutional neural network algorithm and SoftMax classifier for multi-class classification.

3.2 ConvNets Architecture

A **Convolutional Neural Network (CNN or ConvNet)** is a Deep Learning algorithm that is capable of taking an image input and assigning a value (learnable biases and weights) to several features in the images which can initiate the differentiation from one another. The required pre-processing in a ConvNet is enormously low in contrast to other classification algorithms. Whereas in primary methods, features are hand-engineered and with adequate training, ConvNets learns these characteristics by itself.

ConvNet is preferred over a feed-forward neural network as it is able to **strongly catch the Temporal and Spatial dependencies** in an image by applying the appropriate filters. Due to the decline in the total number of parameters connected and reusing the ability of weights, the architecture presents an apt fixture of the image dataset. In simpler words, for a better knowledge of refinement of the image, the network can be trained. Figure 3 represents the ConvNet architecture designed by us.

The Four main layers used in ConvNets architecture is listed as below:

- **Convolution**: The main advantage of the Convolutional technique in ConvNets is for differentiating appropriate features from the image that can act as an input for the initial layer. The spatial interrelation of the pixels is provided by the convolution [8]. Figure 4 shows the convolution of a matrix using (3, 3) as its

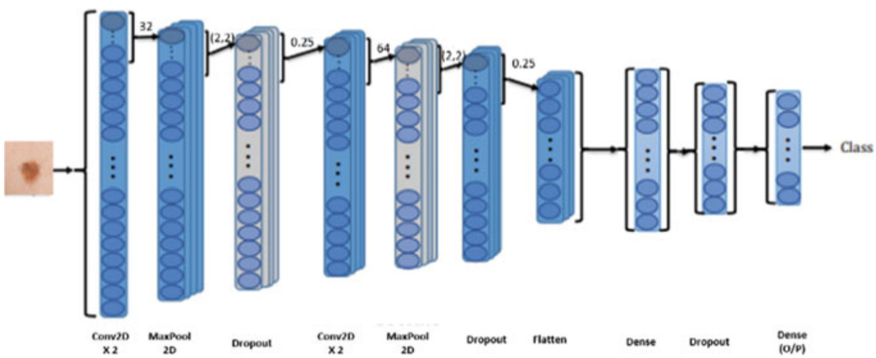

Fig. 3 Architecture of CNN

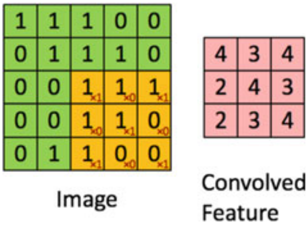

Fig. 4 Convolution of a matrix

kernel size. Equation (1) gives the statistical representation for convolution of a matrix.

$$I\_new(x, y) = \sum_{j=-1}^{1} \sum_{i=-1}^{1} a_{ij} I\_old(x - i, y - j) \quad (1)$$

- **Activation Function**: Rectified Linear Unit ReLU is used in the model to increase non-linearity in the ConvNet and it acts on a fundamental step. In other words, it is an advancement that is implemented per pixel and outmodes the non-positive values of every pixel, hence mapping the feature by zero. It is an uniform approximation and is used for multiclass classification in our model [9]. Figure 5 shows the graph of the ReLU function. Equation (2) represents the ReLU function.

$$R(x) = \max(0, y)\text{n} \quad (2)$$

- **Pooling**: Spatial Pooling, also known as subsampling or downsampling benefits in the reduction of the dimensions of each feature mapping but while doing so, it retains the most significant information of the map. MaxPool helps in finding the maximum value of the pixels present in the provided kernel size, thus enhancing the features available in the sample [10]. After pooling is done, our three-dimensional feature map gets converted to the single-dimensional column

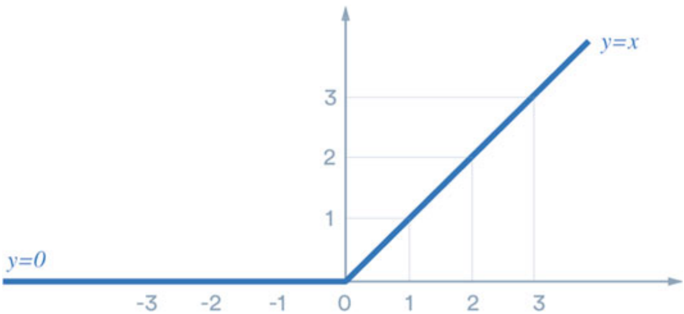

Fig. 5 ReLU function

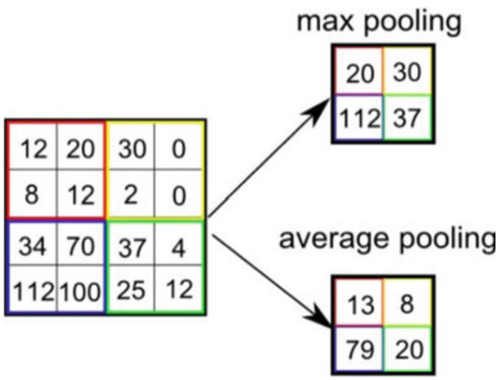

Fig. 6 MaxPool and average pooling of a matrix

vector. Figure 6 shows the max pooling and average pooling of a matrix using (2, 2) as kernel size.

- **Flatten**: Flattening is an essential step in ConvNets. Flattening is done as soon as the pooled featured map is obtained. It involves modification of the complete pooled feature mapped matrix into a single column. Furthermore, it is fed to the artificial neural network for processing. Figure 7 is a matrix representation of the technique used in flattening.
- **Classification (Fully Connected Layer)**: After flattening is done, the flattened feature mapped matrix is sent through a fully connected neural network. This step is a combination of the fully connected layer and the output layer. The fully connected layer is alike the hidden layer in artificial neural network's but in this case, it's fully connected. We get the predicted classes at the output layer. The error of prediction is calculated on the basis of the passed information. Then backpropagation of error is done through the system in order to improve the weights and the biases. Figure 8 shows the connections between fully connected layer/dense layer.

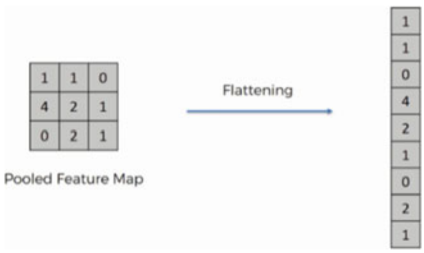

Fig. 7 Flatting of a matrix

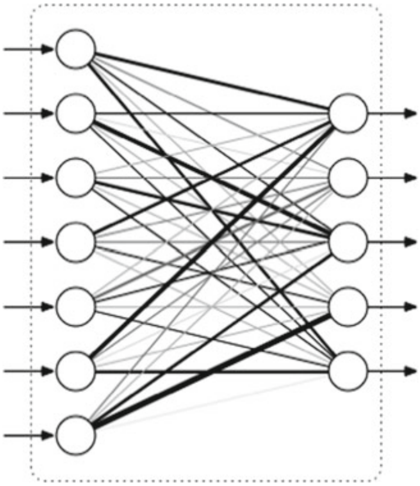

Fig. 8 Fully connected layer

4 Results and Discussions

This research comprises of six diagnosis classes as mentioned in the database description. As transcribed earlier in the section of 'A brief overview on related works', some researchers stated several techniques for diagnosing skin disease. The accuracies reported by them vary between 50 and 90%.

The database used in our whole system consists of 1600 samples of which around 1400 are complete samples used for training and validating the ConvNet model and 180 images are samples with missing attributes used for gaining testing accuracies. Of 1400 samples, 85% of the database was used for training the ConvNet and rest of the database (15%) was used for validating the proposed system.

The confusion matrix in the heatmap form demonstrates the classification results of the system. In this matrix, each cell contains the analogous accuracies of exemplars classified for the corresponding combination of desired and actual network outputs [11]. Figure 9 gives the confusion matrix displaying the classification results of this network. The y-axis and x-axis denote the labels of actual and predicted classes. The vertical scale in Fig. 9 denotes the color to the accuracy pattern in the heatmap.

Figure 10 shows the AUC curve i.e. accuracy curve and loss function. It shows how accuracy was eventually increased on training epochs. As it displays, we've successfully achieved an accuracy of 93.063% on a testing dataset containing a total of 180 images of different classes. Also, the loss function plot shows the avoiding of overfitting throughout the processing (training). The AUC score obtained from training is 0.841664.

Table 1 shows the report of classification used for assuring the classification quality. The report presents the principal classification metrics support, F1-score, recall, and precision on a per-class basis.

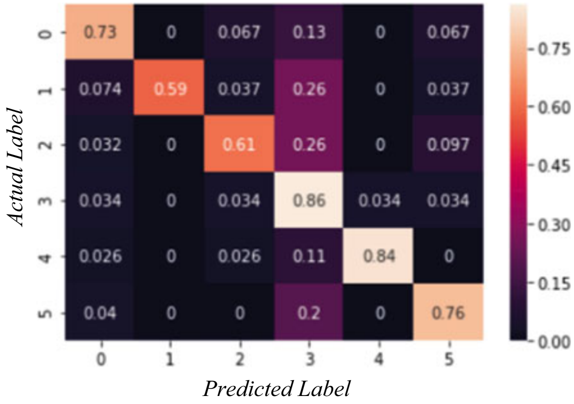

Fig. 9 Confusion matrix

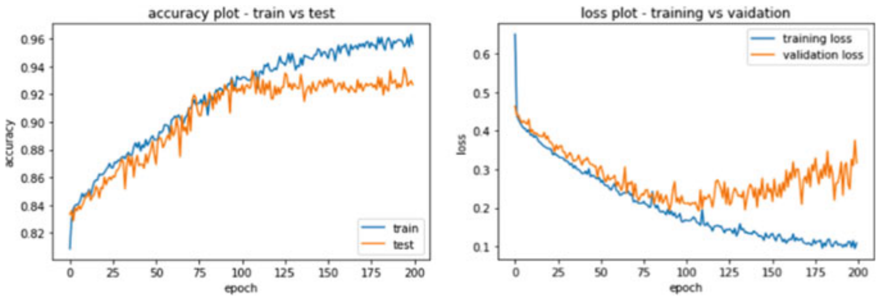

Fig. 10 Accuracy and loss plot

Table 1 Classification report

	Precision	Recall	F1-score	Support
0	0.793	0.767	0.780	30
1	1.000	0.615	0.762	26
2	0.800	0.625	0.702	32
3	0.481	0.862	0.617	29
4	0.970	0.842	0.901	38
5	0.760	0.760	0.760	25
Accuracy			0.750	180
Macro avg	0.801	0.745	0.754	180
Weighted avg	0.807	0.750	0.760	180

- Precision—Ability of a classifier not to label an occurrence positive that is negative.
- Recall—Ability of a classifier to find all positive occurrence.
- F1 score—Weighted harmonic mean of precision and recalls.

The overall F1-score of our model is 0.750, tested on 180 images.

5 Limitations

- No predictions can be made in absence of any skin disease due to the unavailability of appropriate dataset for normal skin.
- No application is available to provide the user with an interface to interact with the model.
- The accuracy of the model can be increased by importing the datasets directly from the hospitals to get more authentic information.

6 Future Scope

- Creating an android application which will be able to make real time predictions.
- Suggesting specialized doctors to the user based on the predictions made by the application.
- Dynamic dataset updating by the doctors so as increase the accuracy of the system.

7 Conclusion

In this paper, we have learned about how the image classification is done using ConvNets. Thus, skin diseases can be diagnosed as well as classified using this technique. Currently, skin diseases have been classified into 6 different types with around 230 images in each class. The experimental results gained a classification accuracy of 93.33% on the testing set. The use of large datasets and advanced computational techniques will help in increasing the accuracy of the system thereby allowing it to suit the results of a dermatologist. This will in turn help in uplifting the quality standards in the field of medicine and research.

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