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Computer Science

CONVOLUTION NEURAL NETWORK CLASSIFIER FOR SKIN DISEASE DETECTION

Ms. Seema Kolkur	Department of Computer Engg, Thadomal Shahani Engg. College, Bandra, Mumbai, India
Dr. D. R. Kalbande	Department of Computer Engg, Sardar Patel Institute of Tech, Andheri, Mumbai, India.
Dr. Vidya Kharkar	Department of Skin and VD, Seth G.S. M.C. & K.E.M Hosp. Parel, Mumbai-400012

ABSTRACT Skin Diseases are becoming very common now days. Number of people suffering from skin diseases is increasing rapidly. Human judgment on diagnosis of skin diseases is sometimes subjective and not reproducible. To achieve more reliable and objective accuracy computer aided diagnosis may be used. Skin disease detection is basically an image classification task. Recently deep learning is used in many image classification tasks. We used Convolution Neural Network (CNN) as a classifier. The results indicate CNN can be feasibly used for skin disease detection. The main advantage of CNN is that we don't need to hand craft features from images, but it learns features on its own.

KEYWORDS : Deep Learning, Convolution Neural Network.

1. INTRODUCTION

Skin diseases are increasingly affecting many all over the world. Due to discoloring and other problems with these diseases, the sufferers face many challenges mentally and socially [1]. Normally a medical diagnosis by experts is required for diagnosis of such diseases. But unfortunately, human judgment is subjective and based on expert's experience in the area. For better objective accuracy, computer aided diagnosis can be very useful.

With the advancement in the field of computer technology and medical imaging, computer aided disease diagnosis and detection is becoming a reality. A machine can find some of the details from images which possibly a human eye cannot. Computers can efficiently read large number of images while humans are error-prone [2]. Different approaches like image processing, data mining and machine learning are used for disease detection in past [3]. Disease Detection is basically a classification task. Accuracy of a classifier depends on feature set used for classification. But, extracting features is very tedious and time-consuming task. CNNs can be a real great help here. CNN can learn features on their own from given large database.

2. RELATED WORK

With current technologies in the field of medical imaging it is easier to acquire multiple good quality images. Many researchers are using images for diagnosis of a disease besides symptoms data. So, Skin Disease Detection is attracting researchers in the field of Machine Learning and Artificial Intelligence. Different types of features are used for such classification systems Texture Features [4-8], Dermoscopic Features [9-12] and Color Features [2,6,13] being commonly used. In most of these disease detection systems Support Vector Machine (SVM) and neural networks with backpropagation are used as classifiers. Skin Cancer and Psoriasis are the mostly widely researched skin diseases.

In recent years, Deep Learning has become very popular choice for image classification tasks. Variants of CNN models have been increasingly achieving better performance in different fields. Authors in [14] and [15] have used CNN for multistage feature extraction for classifying digits in house numbers and music genre classification respectively. One of the commercially popular and successful implementation of CNN is to detect diabetic retinopathy [16-17]. CNN have been successfully implemented for classifying images of Interstitial Lung Disease (ILD) [18-19].

3. METHODOLOGY

Fig. 1 shows general methodology of the proposed system. The system can be broadly categorized into data collection, preprocessing, feature extraction and classification modules. The system takes training and testing set of images as inputs and outputs probability of occurrence of the two diseases.

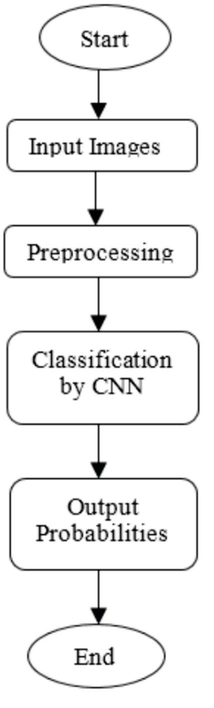


Fig.1 Methodology of Proposed Work

3.1 Data Collection

We have collected our dataset of raw images for two skin diseases mainly Leprosy and Warts from the department of Skin and VD from KEM Hospital, Parel Mumbai. Table 1 shows image dataset description.

Table 1. Dataset Description

Sr. No.	Disease / No of Samples	Training	Testing	Total
1	Leprosy	100	14	114
2	Warts	100	05	105

3.2 Image Preprocessing

Following preprocessing techniques are applied to all the images collected.

- Cropping: Every image is manually cropped to concentrate on diseased body area. Cropping of images is very important as size of images is very large. Fig. 2 shows results of cropping operation.

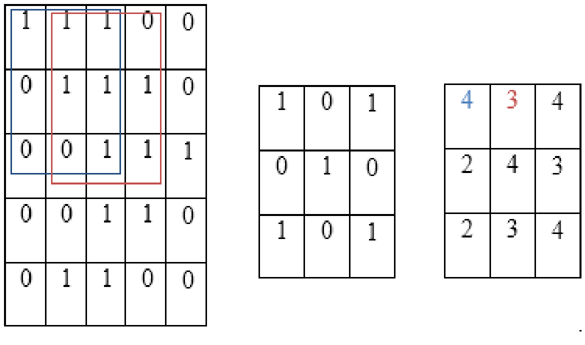
Fig. 2 Image before and after cropping

- Resizing: All the cropped images are saved as 64*64 pixels for maintaining uniformity in dimensions.

3.1 Classification by CNN

CNN are biologically-inspired variants of Multiple Layer Perceptron (MLP). A CNN consists of different types of layers. Each layer has a specific kind of function. It consists of one input and one output layer. In between these two layers there may be multiple hidden layers. The hidden layers typically consist of convolution layers, pooling layers, fully connected layers and dropout layers. Output of every layer acts as an input to next layer [19].

A. Convolution Layer:
Convolution layer is key principle in CNN. Primary purpose of convolution layer is to extract low level features from an input image. It learns the spatial relationship between pixels to learn image features using small squares of input data called filter/kernel [20]. It uses a convolution operator. A filter slides over an input image. Convolution operator computes point-wise multiplication of input image pixels and filter pixels and adds these multiplications to get final number as an output. Assuming matrix in 3a) is an input image and 3b) is filter image 3c) represents convolved feature. First cell of 3c) matrix is computed as (1*1+1*0+1*1+0*0+1*1+1*0+0*1+0*0+1*1 =4). CNN initializes and learns the values of these filters on its own during the training process.

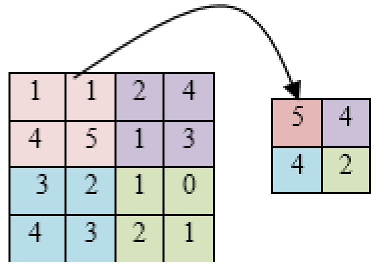


a) Input Image b) Filter c) Convolved Image

Fig. 3 Convolution Operator

B. Rectified Linear Unit (ReLU) Activation
An operation called ReLU is applied after every convolution. ReLU operation, changes all negative values in convolved image to zero and retains only positive values. This introduces non-linearity in network architecture [21].

C. Pooling Layer
It is also called as downsampling/subsampling and is used to reduce the dimensionality of each feature map retaining the most important information. Pooling can be of different types like maxpooling, average pooling or sumpooling. Maxpooling is more commonly used. It simply calculates largest element from a fixed size window (eg. 2X2) from input image and replaces the window in output image with this largest number [22]. In average pooling, instead of largest number average is chosen. Fig 4 shows working of pooling operation with window size of 2x2. First cell of fig 4b) is calculated as max (1,1,4,5).



(a) (b)

Fig. 4 Maxpooling Operation with 2x2 window

D. Drop-out Layer
Drop-out Layer is introduced to improve performance during training. It randomly disables some neurons in each layer. It is equivalent to set some of input values to zero. This helps in avoiding overfitting of the network. Even if some of the neurons are disabled the network should still learn the input pattern [23]. Fig. 5 shows Drop-out effect on network architecture [24].

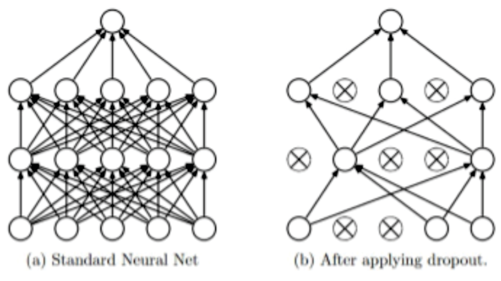


Fig. 5 Dropout Layer

E. Fully Connected Layer
It is also called as dense layer and is like a traditional MLP where every neuron in the previous layer is connected to every neuron in this next layer. The Fully Connected layer is normally used at the end of architecture to combine features learnt from lower layers. It uses a softmax function to calculate probabilities for multiclass classification. We used binary cross-entropy as we have only two output classes.

F. Output Layer
Output Layer has number of neurons representing output parameters/conditions.

Table 2 describes architecture of our network. We have used two convolution layers, two maxpooling and two dropout layers and one dense layer. Input is 64x64 RGB image and output layer has two units representing two skin diseases. Convolution layer uses 32 filters of 5x5 size with maxpooling of size 2x2. Fig. 6 gives graphical representation of our architecture.

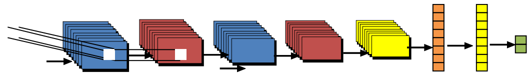


Fig. 6 Network Architecture

Table 2. CNN Layer Description

Sr. No.	Layer Name	Size
0	input	3x64x64
1	conv2d1	32x60x60
2	maxpool1	32x58x58
3	conv2d2	32x54x54

4	maxpool2	32x52x52
5	dropout1	32x52x52
6	Dense	256
7	dropout2	256
8	Output	02

4. RESULTS

The image dataset was divided in training and testing dataset as shown in table 1. CNN model was trained to fit to training data. It outputs probability of every test record being classified as either Leprosy or Warts. Table 3 shows confusion matrix for the testing set.

Table 3. Confusion Matrix

		Predicted	
		Leprosy	Warts
True	Leprosy	13	1
	Warts	0	5

Normally, precision and recall measures are used for evaluating performance of a classifier. Some Systems also use sensitivity, specificity and accuracy as evaluation criteria which are calculated using equations 1,2,3.

$$Sensitivity = \frac{TP}{TP+FN} \quad (1)$$

$$Specificity = \frac{TN}{TN+FP} \quad (2)$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (3)$$

Table 4. Performance Metrics

	precision	recall	f1-score	Support
Leprosy	1.00	0.93	0.96	14
Warts	0.83	1.00	0.91	05
avg / total	0.96	0.95	0.95	19

As can be seen from table 3 and 4 accuracy, specificity and sensitivity of classifier is 95%, 100% and 93% respectively.

We can also visualize what filters were used during the training process. Fig.7 shows 32 filters used in first convolution layer. There are three such sets of 32 filters for a RGB image corresponding to three color dimensions.

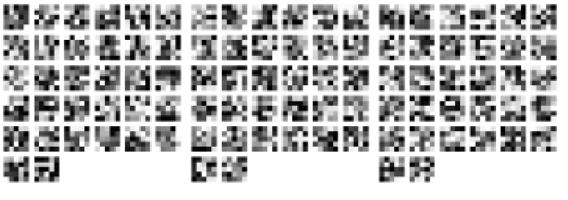


Fig. 7 32 features of size 5X5 from first layer

During batch-wise training, training data is further divided into training and validation in 80-20% ratio. Fig. 8 shows how training loss, validation loss and validation accuracy changes during training process. As can be seen in 8a) training loss decreases as number of increase. As validation accuracy increases, validation loss goes down when number of epochs increases (fig 8b).

5. DISCUSSION

Deep learning and CNN is used in some computer aided diagnosis systems which are based on medical image analysis. In [18, 19] authors have used CNN to classify images of Interstitial Lung Disease (ILD) [18-19].

To the best of our knowledge, no work on classification of skin disease images using CNN is carried out till date. Researchers have used pretrained CNN models for feature extraction but not for classification. In [25] AlexNet was used for feature extraction in skin cancer detection. Major contribution of our work lies in collection of primary data and training a new network from scratch feature for extraction. Our system can be used as preprocessing tool for extracting features from a large set of input images before any classification algorithm.

6. CONCLUSION

We have used convolution network as a classifier for skin disease detection from an input image. The overall accuracy of classification is 95% which shows CNN can successfully be used for the stated purpose. Major advantage of a system is that we do not have to extract features from the set of input images separately. CNNs learn features on their own. Convolution layer and pooling layer acts as feature extractor while dense layer works as classifier.

Fig. 8 a) Training Loss

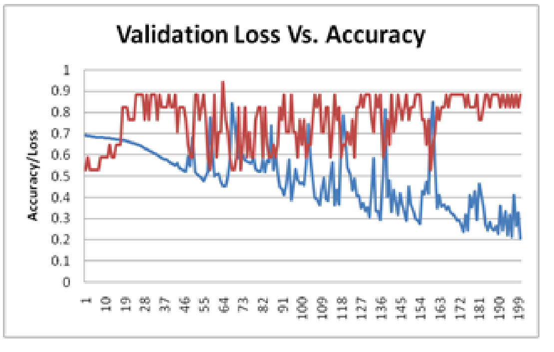


Fig. 8 b) Validation Accuracy Vs. Loss

The accuracy can further be improved by adding more number of images and/or by adding more number of layers in CNN architecture. By adding two drop-out layers we make sure the network does not overfit. This system can be further extracted to classifying multiple skin diseases.

Preprocessing of images is very important task. Currently, we manually cropped images. This process can be automated by using some image processing techniques like object localization and segmentation.

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