Diabetic Retinopathy Using Deep Learning

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Abstract- *Retinopathy is very important in detection of diabetic vision loss. This paper is for methodology for diabetic retinopathy detection from eye fundus images using a generalization of the deep learning method. We formulate the BoVW as two convolutional neural networks that can be trained jointly. Unlike the BoVW, our work able to learn how to perform feature extraction, feature encoding, and classification under guidance of the classification error.. Experimental results shows that CNN gives average aprox. 96.00 % results.*

Keywords- Convolutional neural networks, Diabetic retinopathy detection

I. INTRODUCTION

Retinal images are widely used by ophthalmologists and primary care physicians for the screening of epidemic eye diseases, such as Diabetic Retinopathy (DR). Early detection and diagnosis of DR is crucial for the prevention of visual loss. Among the early signs of DR, Micro Aneurysms (MAs) are the first signs of the presence of DR. Therefore, their detection is of paramount importance for the early diagnoses of DR [1][2].

There is different old techniques e.g. Electrophysiological testing, Electroretinogram (ERG), Electrooculogram (EOG), which is use for detection of DR (micro aneurysms), but these techniques can't detect early & in real time system[3].

The detection of micro aneurysms in digital color fundus photographs is a critical first step in automated screening for diabetic retinopathy (DR), a common complication of diabetes. Diabetic retinopathy (DR) is the damage caused by complications of diabetes to the retina. This is one of the leading causes of blindness across the world [4]

Micro Aneurysm incidence rates have been increasing for the past few decades. MAs are a small dilation of retinal capillaries due to the weakness of the vessel walls. On the retinal surface, they appear as small round dark red dots with about 10 to 100μm in diameter [5].

Early diagnosis of micro aneurysm increases the chances for cure significantly in real time system. If we don't detect it early then there is chances of vision loss.

Worldwide, the prevalence of diabetic retinopathy (D.R.) is increasing at an alarming rate [6]. World Health Organization (WHO) has predicted that in India, the number of adults with diabetes will be highest in the world.

The major cause of diabetes in India is because of the impact of rapid urbanization, industrialization, lack of exercise, unnourished food, and life style changes has led to an increasing prevalence of diabetes and its associated complications such as neuropathy, vascular diseases (cardiac, cerebral and peripheral) and retinopathy indeed [5][6].

Hence, an accurate, premature diagnosis of DR is an essential task because of its potentiality for reducing the number of cases of blindness across the globe. In this paper we present a procedure to detect the presences of abnormalities in the retina such as micro aneurysms, exudates using rule based system.

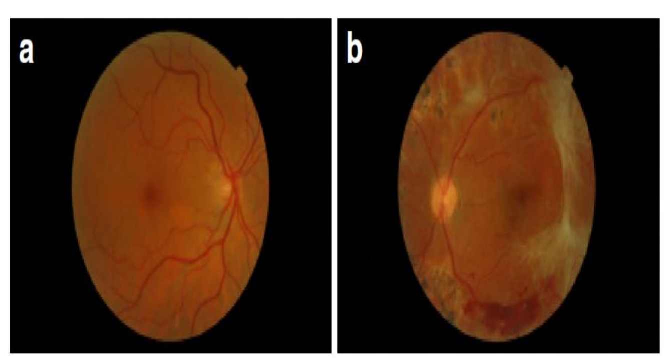

Fig. 1 a) Normal Image b) Diabetic Image

Diabetic retinopathy (DR) is a complication of diabetes mellitus, wherein micro aneurysms start to form in the small vessels of the retina. In later stages of the disease, some retinal blood vessels may get blocked causing vision loss. Patients often do not have symptoms of the disease in its beginning stages which makes early diagnosis hard.

DR is leading cause of blindness and visual loss in the working age population and the second most common cause in the USA [7]. Early detection of diabetic retinopa-thy is paramount for the success for treatment, as it can prevent up to 97% of severe vision loss [8].

First way of performing the diagnosis of DR is by visu-ally inspecting eye fundus images in order to detect retinal lesions. Examples of eye fundus images were took from the Messidor [9] dataset and it will be seen in Fig. 1. Although there are several grades of DR, we are focusing in the task of detecting the disease.

The paper is divided in five parts: The first part is an introduction including previous research on diabetic retinopathy. The second part is for the system methodology including CNN. The third part provides experimental results for normal and retinal images. Last section concludes the work.

II. SYSTEM METHODOLOGY

The block diagram of the proposed methodology is shown in following figure,

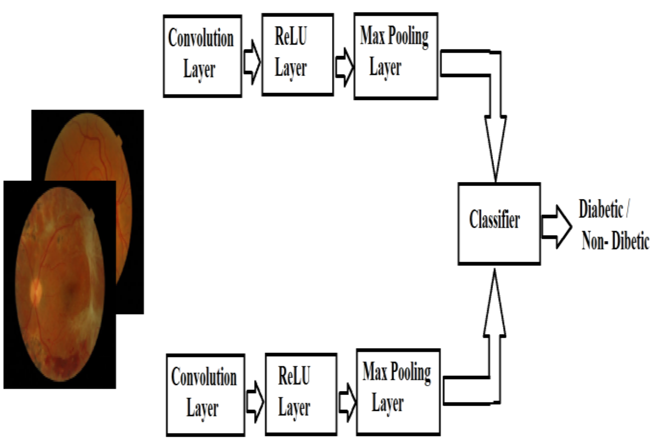

Fig 2. Proposed system block diagram

In machine learning, a network (CNN, or ConvNet) is a class of deep, feed-forward artificial neural networks, CNNs use a variation of multilayer perceptrons designed to require minimal preprocessing. Convolutional networks were inspired by biological processes[4] in that the connectivity pattern between neuronsresembles the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field. CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand-engineered. This independence from prior knowledge and human effort in feature design is a major advantage. They have applications in image and video recognition, recommender systems and natural language processing. A CNN consists of an input and an output layer, as well as multiple hidden layers. The hidden layers of a CNN typically consist of convolutional layers, pooling layers, fully connected layers and normalization layers.

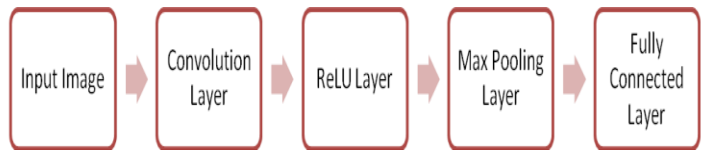

Fig 3.1 CNN architecture

Convolutional Layer

Convolutional layers issue to apply a convolution operation to input, and passes the result to next layer. This layer performs convolution of input images and filter kernel which gives interconnectivity between image region.For instance, a fully connected layer for a (small) image of size 100 x 100 has 10000 weights for *each* neuron in the second layer. Each filter is convolved against the input image and extract the features by forming a new layer or activation map. Each activation map contain or represent some significant characteristic or features of the input image

In this way, it resolve a vanishing in training traditional multi-layer neural networks with many layers by using backpropagation

ReLU Layer

Rectified Linear Unit is used as activation function in CNN. This layer truncates negative values to zero to remove non-linearity.This is use to increases the nonlinear properties of the decision function and of the overall network without affecting the receptive fields of the convolution layer. ReLU removes the nonlinearity in the CNN layer output

Max Pooling Layer

This is one of the most significant layer which helps the network from avoiding over-fitting by reduce the parameters and computation in the network.Another important concept of CNNs is pooling, which is a form of non-linear down-sampling. There are several non-linear functions to implement pooling among which *max pooling* is the most common. It partitions the input image into a set of nonoverlapping rectangles and, for each such sub-region, outputs the maximum. The intuition is that the exact location of a feature is less important than its rough location relative to other features. The pooling layer serves to progressively reduce the spatial size of the representation, to reduce the number of parameters and amount of computation in the network, and hence to also control overfitting. It is common to periodically insert a pooling layer between successive convolutional layers in a CNN architecture. It works as a form of non-linear down sampling. Pooling partition the activation maps into set of rectangles and collect the maximum value in the sub region. It's merely a downsize the pixels with features. For instance, if **NxN** input layer, that will give output layer of **N/K:**

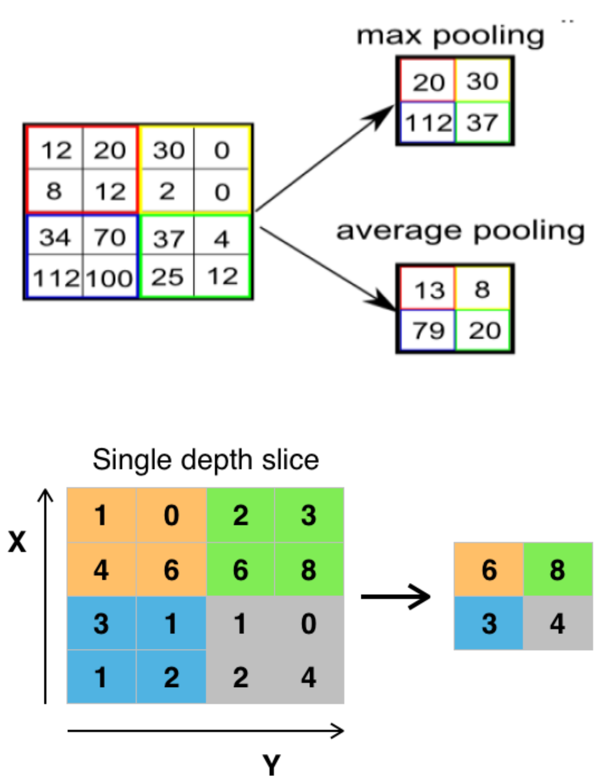

Fig 3.2. Maximum Pooling

The pooling layer operates independently on every depth slice of the input and resizes it spatially. The most common form is a pooling layer with filters of size 2x2 applied with a stride of 2 downsamples at every depth slice in the input by 2 along both width and height, discarding 75% of the activations. In this case, every max operation is over 4 numbers. Due to the aggressive reduction in the size of the representation, the trend is towards using smaller filters[42] or discarding the pooling layer altogether

Fully connected

The layer which comes after the cascaded convolutional and max/average pooling layer is called Fully connected layer.

Fully connected layers connect every neuron in one layer to every neuron in another layer. It is in principle the same as the traditional multi-layer perceptron neural network. In neural networks, each neuron receives input from some number of locations in the previous layer. In a fully connected layer, each neuron receives input from *every* element of the previous layer. In a convolutional layer, neurons receive input from A fully connected layer takes all neurons in the previous layer from max-pooling layer and connects it to every neuron it has. Fully connected layers are not spatially connected anymore. It visualize as one-dimensional layer.only a restricted subarea of the previous layer. In a convolutional layer, the receptive area is smaller than the entire previous layer.

III. EXPERIMENTAL RESULTS

For the implementation we have used eye retina images in cross-sectional view . We have collected 80 diabetic and 120 non diabetic eye retina images from DRINOS dataset and 150 normal images and 100 diabetic images from DRIVE database. Resolution of each image in database is 530X298 pixels. few samples are shown in the following figure.

Figure sample database images (DRINOS)

As original image is color image, it is converted to gray scale image to save the time and memory. Gray scale image is provided to the CNN layer 1 as the input. Color image has three planes for red, green, and blue. Figure 4.3 shows the color and gray scale image.

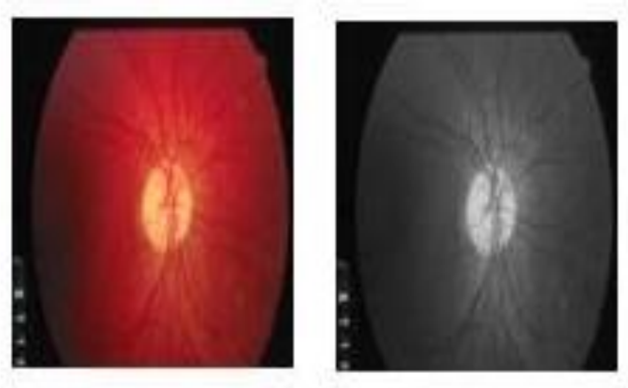

Figure 4.3 Color and Gray scale image

The output layers for different layers of CNN are shown in the figure 4.4 to 4.6.

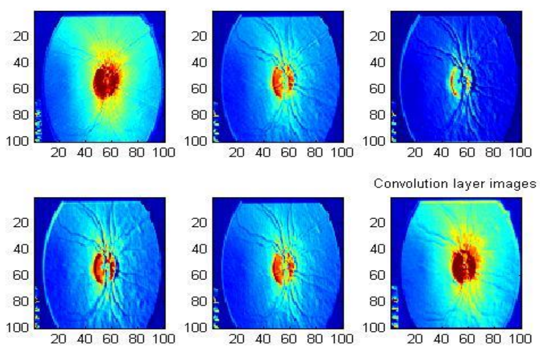

Figure 4.4 Convolution layer output

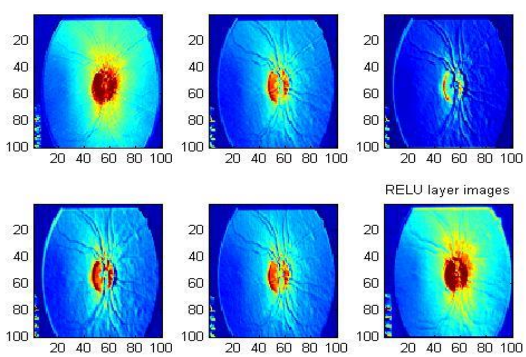

Figure 4.5 ReLU layer output

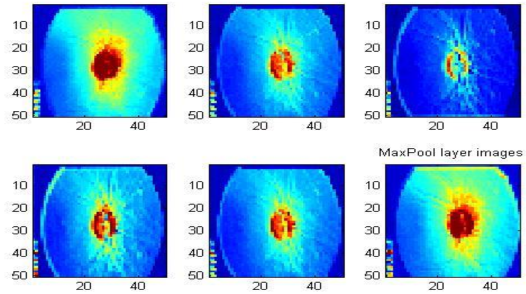

Figure 4.6 Max pooling layer output

The performance of the system is computed on the basis of the percentage accuracy for DRINOS and DRIVE retinal fundus images. The accuracy is computed using equation.

Accuracy = (Correctly Recognized samples / Total samples) * 100

The accuracy for the DRINOS and DRIVE database is shown in the following table I and table II.

Table I. Accuracy in % for DRINOS Database (DNN 3 layers)

Database	**Total Test samples**	**Correctly Recognized samples**	**% Accuracy**
Normal Images	120	117	97.50 %
Diabetic (Glaucoma) Images	80	78	100 00 %
Average Accuracy			**98.75 %**

Table I. Accuracy in % for DRIVE Database (DNN 3 layers)

Database	**Total Test samples**	**Correctly Recognized samples**	**% Accuracy**
Normal Images	150	147	98.00 %
Diabetic (Glaucoma) Images	100	96	96. 00 %
Average Accuracy			**97.00 %**

IV. CONCLUSION

In this paper we are going to proposed convolutional neural network is applied to retinal fundus images to detect the diabetic retinopathy. Nonlinearity in CNN is removed with the help of rectified linear unit layer as well as features are reduced using maximum pooling layer.

Deep neural network is simple and robust feature extraction algorithm which shows the interconnectivity between the image regions. Extensive experimentation are carried on the total 200 images from DRINOS database. Experimental results show that deep convolutional neural network gives 96.50 % accuracy.

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