Classification of Diabetic Retinopathy Using Deep Learning

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Abstract- *The diagnosis of diabetic retinopathy (DR) through colour fundus images requires experienced clinicians to identify the presence and significance of many small features which, along with a complex grading system, makes this a difficult and time consuming task. In this paper, we propose a CNN approach to diagnosing DR from digital fundus images and accurately classifying its severity.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. In this paper, we demonstrate the use of convolutional neural networks (CNNs) on color fundus images for the recognition task of diabetic retinopathy staging. Our network models achieved test metric performance comparable to baseline literature results, with validation sensitivity of 95%. We additionally explored multinomial classification models, and demonstrate that errors primarily occur in the misclassification of mild disease as normal due to the CNNs inability to detect subtle disease features. 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].

In this paper we introduce an automatic DR grading system which is capable of classifying images based on disease pathologies from four severity levels. A convolutional neural network (CNN) convolves an input image with a defined weight matrix to extract specific image features without losing spatial arrangement information. We initially evaluate different architectures to determine the best performing CNN for the binary classification task and aim to achieve literature reported performance levels. We then seek to train multi-class models that enhance sensitivities for the mild or early stage classes, including various methods of data preprocessing and data augmentation to both improve test accuracy as well as increase our effective dataset sample size. We address concerns of data fidelity and quality by collating a set of ophthalmologist verified images. Finally, we address the issue of insufficient sample size using a deep layered CNN with transfer learning on discriminant color space for the recognition task. We then trained and tested two CNN architectures, AlexNet and GoogLeNet, as 2-ary, 3-ary and 4-ary classification models. They are tuned to perform optimally on a training dataset using several techniques including batch normalization, L2 regularization, dropout, learning rate policies and gradient descent update rules[3]. Experimental studies were conducted using two primary data sources, the publicly available Kaggle dataset of 35,000 retinal images with 5-class labels (normal, mild, moderate, severe, end stage) and a physician-verified Messidor-1 dataset of 1,200 color fundus images with 4-class labels. Throughout this study we aim to elucidate a more effective means of classifying early stage diabetic retinopathy for potential clinical benefits.

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.

complications such as neuropathy, vascular diseases (cardiac, cerebral and peripheral) and retinopathy indeed [5][6].

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.

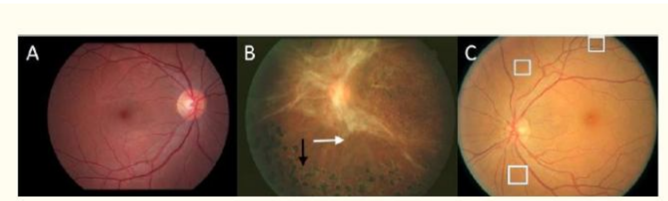

Fig. 1 Representative retinal images of DR at various stages of the disease, as labeled: A- normal, B- end stage, C- early stage. Arrows in B point to pathological indications. White boxes in C enclose very small lesions that the CNNs have difficulty discerning

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. LITERATURE REVIEW

Many conventional methods, Machine Learning techniques and few Deep Learning approaches have been attempted for Diabetic Retinopathy detection.

• Review on Conventional Methods:

– Argade et al. proposed Image Processing and Data Mining Techniques for automatic detection of Diabetic Retinopathy [3].

– Mukherjee et al. proposed another conventional technique. The methodology followed by them included Image Processing which involves background normalization and contrast enhancement using histogram equalization. It is followed by Optical Disk Detection, Blood Vessel Extraction and Exudate Detection [4].

• Review on Machine Learning Techniques:

– Bhatia et al. proposed a Machine Learning Model for diagnosis of Diabetic Retinopathy using ensemble of classification algorithms, alternating decision tree, AdaBoost, Naive Bayes, Random Forest and SVM and achieved a maximum accuracy of 90 %, sensitivity of 94 % and F1-score of 90 % [5].

– Labhade et al. applied soft computing techniques for Diabetic Retinopathy Detection in which they used different classifiers like SVM, Random Forests, Gradient boost, AdaBoost, Gaussian Naive Bayes [6].

– Mohammadian et al. proposed a comparative anal- ysis of 9 common Machine Learning Classification Algorithms for Diabetic Retinopathy Detection [7].

• Review on Deep Learning Approaches:

– Doshi et al. proposed a Deep Learning Approach involving a Deep Convolutional Neural Network with a specific Network Architecture obtaining a Quadratic Kappa Score of 0.3996 [8].

– Xu et al. applied Deep Convolutional Neural Net- works for early automated detection of Diabetic 2 Retinopathy and achieved a highest accuracy of 94.5% [9].

– Gargeya et al. proposed a Deep Learning Model for identification of Diabetic Retinopathy and achieved a Sensitivity of 0.93, Specificity of 0.87 and Area Under the Receiver Operating Characteristic Curve of 0.94 [10].

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III. PROPOSED METHODOLOGY

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

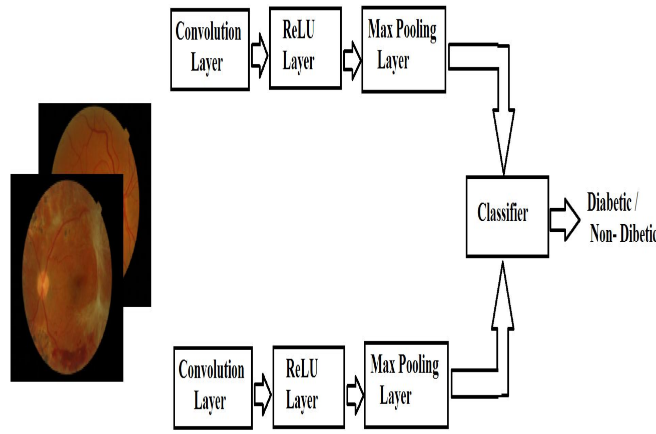

Fig 3.1. Proposed system block diagram

i)**Conversion to Weighted greyscale**: As all the images which were colour (RGB) initially, were converted to greyscale by taking a weighted average of the RGB pixels in which 0.299 of the Red (R) Component, 0.587 of the Green (G) Component and 0.114 of the Blue (B) Component are considered.Conversion to Weighted greyscale: As all the images which were colour (RGB) initially, were converted to greyscale by taking a weighted average of the RGB pixels in which 0.299 of the Red (R) Component, 0.587 of the Green (G) Component and 0.114 of the Blue (B) Component are considered.

$$I = R * 0 \cdot 299 + G * 0 \cdot 587 + B * 0.114$$

where I is the Resultant Pixel

ii)Resizing: All the converted greyscale images are resized to a fixed size of 1000x1000 pixels.
Pixel Rescaling: For every image, each and every
pixel values are rescaled into a value between 0 and 1 by dividing by 255 for easy computation.

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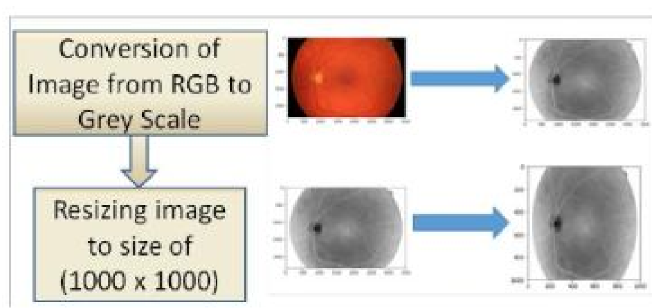

Fig 3.2. Image Transformations in Pre-Processing

Features to Distinguish between a healthy and a non-healthy eye

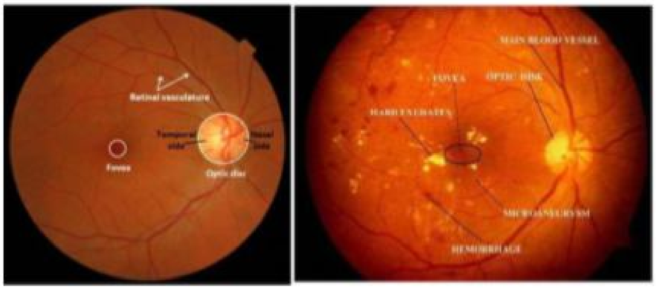

Fig.3.3 FUNDUS images features

The hidden layers of a CNN typically consist of convolutional layers, pooling layers, fully connected layers and normalization layers.

True Positive(TP) - Correctly dete cted DR images
True Negative (TN) - Correctly detected Non-DR images
False Positive(FP) - Number of Non-DR images are detected wrongly as DR imag s False Negative(FN) - Number of D R images are detected wrongly as Non-DR ima ges

At last, the Sensitivity, Specificity, and Accuracy are measured for each fundus ima ges available in the database.

SE = TP / TP + F N SP = TN / TN + FP

Accuracy = TN + TP / TN + FP + FN + FP Precision = TP / TN + TP

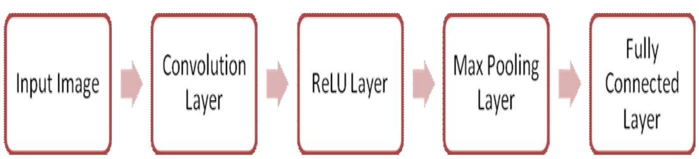

Fig 3.4 CNN architecture

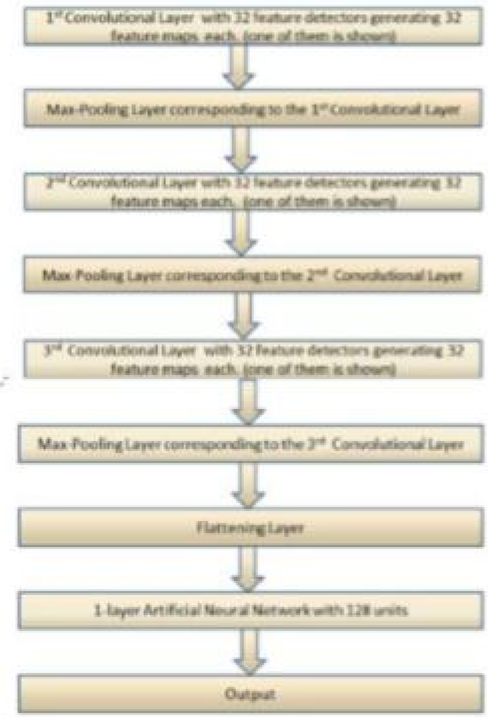

Fig.3.5 Summary of CNN layers

Convolutional Layer

Convolutional layers issue to apply a convolution operation to input, and passes the result to next layer.. Each filter is convolved against the input image and extract the features by forming a new layer or activation map.

In this way, it resolve a vanishing in training traditional multi-layer neural networks with many layers by using backpropagation. A small example of a Convolutional Layer is described in Fig 4.

$$(f * g)(t) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} f(\tau)\, g(t-\tau)\, d\tau$$

Fig.3.5.1Convolution operation

ReLU Layer

Rectified Linear Unit is used as activation function in CNN. This layer truncates negative values to zero to remove non-linearity. ReLU removes the nonlinearity in the CNN layer output. ReLU Layer or Rectification Layer: ReLU is Rectified Linear Unit defined as shown in Fig 5.

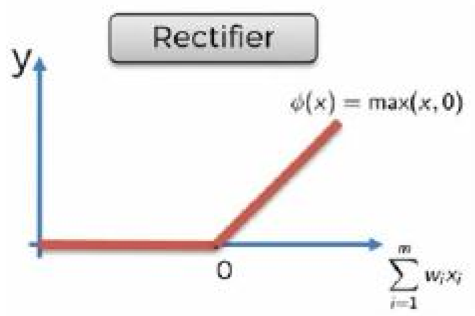

Fig.3.6 Defination of ReLU

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. For instance, if **NxN** input layer, that will give output layer of **N/K:**

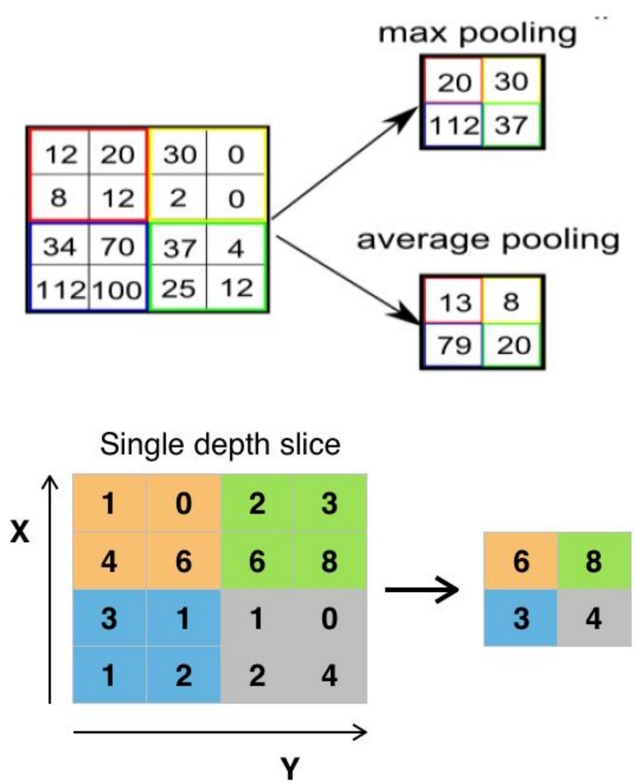

Fig 3.7. Maximum Pooling

The pooling layer operates independently on every depth slice of the input and resizes it spatially. Max-Pooling operation is described in Fig 6

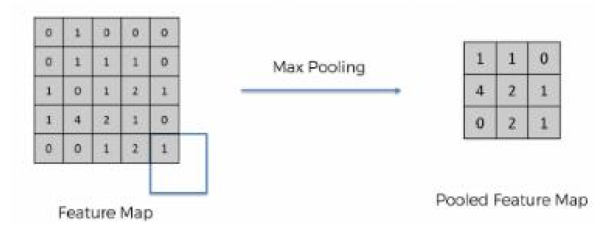

Fig.3.8 Example of a Max-Pooling Layer taking a pooling stride of 2x2 dimension

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.

Fig.3.9 Network architecture

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 %**

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