A framework for the Diagnosis of Diabetic Retinopathy Using Deep Learning Techniques

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Abstract--- *Diabetic retinopathy or diabetic eye disease is a medical condition which manifests itself in the retina of the human eye. The effects of the rudimentary stages of this disease include blurred vision, seeing dark spots due to accumulation of blood vessels, and later stages of this disease can cause complete blindness in 90% of cases. The detection and diagnosis of diabetic retinopathy is well established in the field of medicine, and it is performed by professionals only. The process is known to be expensive and cumbersome. However, the rise of machine meaning and AI has paved the path towards disease detection, creating a niche for diabetic retinopathy detection. This paper presents a deep learning-based framework for the diagnosis and detection of diabetic retinopathy.*

Keywords--- *Learning Techniques, Diagnosis of Diabetic, Retinal Barrier.*

I. INTRODUCTION

Diabetic retinopathy is one of the largest causes of blindness in adults. It is prevalent in adults who have diabetes. The disease manifests itself when the patient has been affected with diabetes for a long duration of time. The symptoms are the leakage of small blood vessels in the eye and dilapidation of nervous tissue. This results in minimal blood flow and also the dysfunction of the neurons in the inner retina. The later stages of this disease are characteristic of mild changes in visual function, eventually leading to partial or total blindness and the dysfunction of the blood – retinal barrier.

Deep learning is a vast extension of machine learning techniques that not only contains on task specific algorithms but also methods based on learning data representations. Deep learning networks are modelled after biological neural networks. They possess a multiple layers of non linear processing units, known as neural layers, each of which uses the output of the preceding layer as the input for itself. Deep learning is classified into supervised and unsupervised learning. The former is used for classification of a dataset into predefined categories and the latter is used to analyse patterns. Neural nets have been further developed and classified into Convolutional Neural Networks (CNNs), Deep Belief Networks, Recurrent Neural Networks (RNNs) etc. Applications of deep learning are machine translation, audio and speech recognition, audio classification, natural language processing etc.

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In this paper, we present a framework for a proposed model for the detection of diabetic retinopathy based on Deep Learning. We take input from a publicly available dataset and pass it through feature extraction algorithms. Then, the features are classified through an intelligence system. Finally, the classification of the disease is performed by the intelligence system and the prediction and diagnosis of the disease may be finished.

II. LITERATURE REVIEW OF RELATED WORK

Publications on the detection and classification of diabetic retinopathy are multitudinous in the realm of research. Many proposed methods in research papers make use of machine learning algorithms, deep learning frameworks, convolutional neural networks (CNNs) and support vector machines (SVMs) to diagnose DR. This section provides a brief overview of the extent to which the deep learning methods have been used.

Romany F. Mansour [1] has made good use of computer aided diagnostics (CAD) for detection of diabetic retinopathy. AlexNet DNN, a tool whose underlying principle is based on Convolutional Neural Networks, was used to enable an optimal diabetic retinopathy CAD solution. The results with the Kaggle fundus datasets reveal that the proposed AlexNet DNN- based DR performs better with LDA feature selection, where it exhibits a DR classification accuracy of 97.93% with FC7 features, while with PCA, it shows 95.26% accuracy.

Juan Shan et.al [2] aimed to detect the microaneurysms in the eye, due to leakage of retinal blood vessels. This particular method employs the use of a Stacked Sparse Autoencoder for microaneurysm detection is mentioned. The dataset used is the publicly available DIARETDB to provide the test data and the training data.

89 images were used, 2182 image patches had microaneurysms lesions, 6230 without. An accuracy of 91.3% and 96.2% was achieved during 10- fold cross valuation.

Darshit Doshi et.al [3] is able to automatically diagnose and classify the five stages of diabetic retinopathy (based on severity) by designing and implementing GPU accelerated deep convolutional neural network. The dataset used in the paper is the free, open sourced, platform for screening DR called EyePACs. The single model accuracy of the convolutional neural networks presented in this paper is 0.386 on a quadratic weighted kappa metric and the working assemblage of three such similar models resulted in a better score of 0.3996.

IgiArdiyantoet.al [4] proposed a deep learning-based low-cost embedded system to assist medical professionals for grading the severity of the DR from the retinal images. The used dataset is the FINDeRS dataset, has a total of 315 images organised into five grades based on severity, 175 images of no DR, 52 of mild NPDR, 32 of moderate NPDR, 18 of severe NPDR, and 38 of PDR. The algorithm achieved the accuracy of 60.28%, sensitivity of 65.40%, and specificity of 73.37%.

RishabGargeyaet.al [5] developed and deployed a data- driven deep learning algorithm as a new diagnostic tool with regard to automated DR detection. The model achieved 0.97 AUC (area under the receiver operating characteristic curve – a metric for accuracy) score with 94% to 98% sensitivity and specificity with the local dataset. The AUC results with the MESSIDOR 2 and E- Ophtha databases were 0.94 and 0.95 respectively.

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III. Architecture Of The Framework For The Diagnosis Of Diabetic Retinopathy

The framework that we propose consists of five stages: image data input, data preprocessing, feature extraction, deep learning classification and prediction and diagnosis of diabetic retinopathy.

A. Image Data Input

Several Publicly available datasets are present in the internet. They include Digital Retinal Images for Vessel Extraction (DRIVE) and Structured Analysis of the Retina (STARE) database, ImageRet database, and ROC micro a neurysm database.

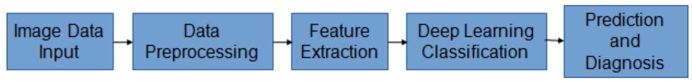

Fig.1.3: Framework of diagnosis and prediction process

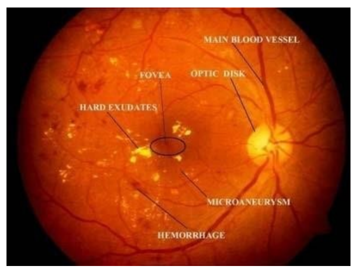

Fig. 1.3.1: A fundus photograph with DR

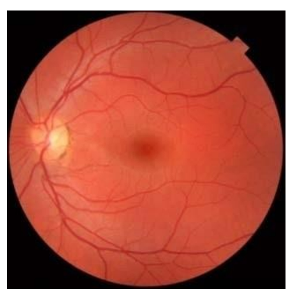

Fig. 1.3.2: A fundus photograph without DR

Pre-processing is required to ensure that the dataset is consistent and displays only relevant features. This step is necessary to simplify the workload of the following processes. Next, the images are segmented to differentiate between the normal and abnormal substances.

Image Data Pre-processing is the process by which raw retinal fundus images are made to be in such a way that they can be fed in into our intelligence system for it to effectively classify them based on their severity. In Diabetic Retinopathy detection they can be done by 2 methods- microaneurysm and haemorrhage based and exudate based. Wang et al. [6] developed a method that achieves 100% accuracy for detecting lesions in retinal images that have abnormalities and 70% in retinal images that are normal. But this system fails to classify the various stages of severity of the disease. Samue et.al [7] proposed for the very first time the classification of abnormalities into-haemorrhages, microaneurysms, hard and soft exudates.

It produced 81.7% accuracy in the NPDR stage. Baudoin [8] was one of the very early persons to detect eye diseases automatically just by observing microaneurysms from FFA images. He combined top hat, match filtering and region growing techniques. Spencer et. al [9] used techniques of morphology like top hat transform for counting of candidate microaneurysms. Walter et. al [10] proposed a process based on top-hat and bounding box closing transforms. His method performs better than Spencer et. al. Gardener et, al [11] proposed the technique of detecting retinal pathologies using neural networks. This method gives very good results on colour fundus images. Now, we'll see exudate based methods. Exudate detection is more difficult because they are very small and also they are colourless. Wang et. al [6] introduced a method of exudate detection using thresholding and shade correction methods but needs user intervention. A much more advanced technique was introduced by Goldbaum et. Al [13] based on edge matching along with template detection by detecting bright lesions as exudates. B.COTE et. Al [12] proposed statistical pixel-based classification method instead of just detecting lesions through template matching.

B. Feature Extraction

In image processing and machine learning, feature extraction is the process of the reduction of dimensionality of the pre-processed input data, i.e., it is reduced into a set of features so that it aids in the following generalization steps.

Feature extraction of fundus images is done through the extraction of retinal vessels. The models of retinal vessel extraction are done, for example, via pattern recognition. Feature vectors were extracted through a supervised method by Niemeijer [103], for every pixel in the green channel of a fundus image.

Match filtering retinal vessel extraction methods include a 2D kernel of images of the retina. A linear-match-filtering based kernel in 2D was developed by Chaudhuri et al.[91] for blood vessel extraction on the DRIVE database. The accuracy achieved is 87.7%.Zana and Klein [100] delineate retinal vessels as piecewise connected; locally linear, bright patterns that upon which a morphological processing method is developed. The work is performed on the DRIVE database, with an accuracy of 93.7%. Martinez-Perez et al.[97] used scale- space analysis of retinal blood vessels that have different breadths at various scales. This segmentation technique is performed on the DRIVE database with an accuracy of 91.8%. Nevertheless, this technique must be validated on a bigger database.

Mathematical modelling also plays a crucial role in the segmentation of the retinal vessel image. Vermeer et al.[106] proposed a profile model that involves Laplace and thresholding technique, succeeded by machine learning classification to improve the technique's execution.

C. Deep Learning Classification

The deep learning classification of the images after feature extraction can be done using artificial neural networks (ANNs), convolutional neural networks (CNNs), and other such methods.

Arditayantoet.al [4] proposed a low cost deep learning based embedded system that assists doctors on the severity of the DR. The algorithm achieved the accuracy of 60.28%, sensitivity of 65.40%, and specificity of 73.37%. AlexNetDNN [1] is an example of the usage of a CNN based tool through which DR classification is done. The results with the Kaggle fundus datasets reveal that the proposed AlexNet DNN- based DR performs better with

LDA feature selection, where it exhibits a DR classification accuracy of 97.93% with FC7 features, while with PCA, it shows 95.26% accuracy.

Gargeya et al. [5] deployed a data driven deep learning algorithm that achieved 0.97 AUC (area under the receiver operating characteristic curve – a metric for accuracy) score with 94% to 98% sensitivity and specificity with the local dataset. The AUC results with the MESSIDOR 2 and E- Ophtha databases were 0.94 and 0.95 respectively.

Implementation

The following architecture was proposed by Darshit Doshi et.al [7][3]

Layers	Model 1	Model 2	Model 3
input	1x512x512	1x512x512	1x512x512
conv 1	16x256x256	16x256x256	16x256x256
conv 2	16x256x256	16x256x256	16x256x256
pool 1	16x128x128	16x128x128	16x128x128
dropout 1	16x128x128	16x128x128	16x128x128
conv 3	32x64x64	32x64x64	32x64x64
conv 4	32x64x64	32x64x64	32x64x64
pool 2	32x32x32	32x32x32	32x32x32
dropout 2	32x32x32	32x32x32	32x32x32
conv 5	48x32x32	64x32x32	64x32x32
conv 6	48x32x32	64x32x32	64x32x32
conv 7	48x32x32	64x32x32	64x32x32
pool 3	48x16x16	64x16x16	64x16x16
dropout 3	48x16x16	64x16x16	64x16x16
conv 8	64x16x16	128x16x16	96x16x16
conv 9	64x16x16	128x16x16	96x16x16
conv 10	64x16x16	128x16x16	96x16x16
pool 4	64x8x8	128x8x8	96x8x8
dropout 4	64x8x8	128x8x8	96x8x8
conv 11	128x8x8	256x8x8	128x8x8
conv 12	128x8x8	256x8x8	128x8x8
pool 5	128x4x4	256x4x4	128x4x4
dropout 5	128x4x4	256x4x4	128x4x4
hidden 1	400	256	256
maxout 1	200	128	128
dropout 6	200	128	128
hidden 2	400	256	256
maxout 2	200	128	128
output	5	5	5

Table 1.4: CNN Architecture of 3 Models

The above mentioned architecture was used. Categorical cross entropy cost function was used. The Adaptive Moment Estimation (Adam (Kingma and Ba 2015) was used as the optimizer. An appreciable accuracy was obtained.

IV. CONCLUSION

Thus, the flow diagram in Figure 1.1 describes the prediction and diagnosis of diabetic retinopathy and if diagnosed, classification of its severity into five stages- no DR, mild NPDR, moderate NPDR, severe NPDR, PDR using retinal fundus images obtained from publicly available datasets is done by our deep learning classifiers.

A fully data-driven artificial intelligence–based grading algorithm can be used to screen fundus photographs obtained from diabetic patients and to identify, with high reliability, which cases should be referred to an ophthalmologist for further evaluation and treatment. The implementation of such an algorithm on a global basis could reduce drastically the rate of vision loss attributed to DR.

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