Diabetic Retinopathy Detection

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***Abstract*— Many Diabetic patients suffer from a medical condition in the retina of the eye known as Diabetic Retinopathy. The main cause of Diabetic Retinopathy is high blood sugar levels over a long period of time in the retina knownas Diabetes Mellitus. The primary goal is to automatically classify patients having diabetic retinopathy and not having the same, given any High-Resolution Fundus Image of the Retina.**

Then, a Deep Learning Approach is applied in which the processed image is fed into a Convolutional Neural Network to predict whether the patient is diabetic or not. This methodologyis applied on a dataset of 1000 High Resolution Fundus Images of the retina. The results, so obtained are a 75 % predictive accuracy and 10% predictive loss. Such an Automated System can easily classify images of the retina among Diabetic and Healthy patients, reducing the number of reviews of doctors.

Keywords*— *Diabetic Retinopathy, Diabetes Mellitus,High Resolution Fundus, Deep Learning, Convolutional Neural Network

I. Introduction

In simple words, Diabetic Retinopathy is an eye disease related to Diabetes. It is a direct consequence of damage of small blood vessels and neurons of the retina. It can lead to swelling and leakage of blood vessels, preventing blood from passing through and also sometimes growth of abnormal new blood vessels in the Retina. Spots or dark strings in vision, blurred vision, fluctuating vision, impairedcolour vision, dark or empty areas in vision and vision loss are absolute symptoms of Diabetic Retinopathy [1]. The various signs and markers of diabetic retinopathy include micro-aneurysms, leaking blood vessels, retinal swellings, the growth of abnormal new blood vessels and damaged nerve tissues. Diabetic Retinopathy can be treated with methods like Focal laser treatment, Scatter laser treatment and Vitrectomy. Surgery often degrades or prohibits the development of diabetic retinopathy, but it is not a complete cure. As it is a lifelong condition, future retinal damage andvision loss is also possible [2]. So, a proper diagnosis of thedisease is a necessity. Diagnosis methods like Fluorescein angiography and Optical coherence tomography which involves external fluid or dies to be applied on to the patients' eye after the Retinal Image is taken. But an Automated System which can immediately predict Diabetic Retinopathy without any external agent, is a more comfortable and convenient method both for doctors and patients.

This paper has been structured as an introduction, literature review, proposed methodology, training the model, details of the learning process, implementation details, resultsand conclusion

II. Literature Review

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

- Review on Conventional Methods:

– Use of IDX-DR machine for automatic detectionof Diabetic Retinopathy [3].

-The IDX-DR consist of several components such as a fundus camera is attached to a computer ,Where the IDX-DR client is installed . By using the fundus camera the patient can take a image of retina through which it will be analysed that a patient have a diabetes retinopathy or not.

– [4].

– Use of eye-injection

For patient with diabetic retinopathy and patients with diabetic macular edema, the recommended dose is 2mg (0.05m L) administrated, fact 80% of patients who received the EYLEA eight week dosing regimen had significant improvement in their diabetic retinopathy.

-Laser treatment and Eye Surgery.

Laser treatment is used to treat new blood vesselsat the back of the eyes in the advanced stages of diabetic retinopathy.

Surgery may be carried out to remove some of the vitreous humour from the eye. This is the transparent jelly like substance that fills the space behind the lens of the eye

- 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-scoreof 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].

Retinopathy and achieved a highest accuracy of94.5% [9].

- Gargeya et al. proposed a Deep Learning Model for identification of Diabetic Retinopathy and achieved aSensitivity of 0.93, Specificity of 0.87 and Area Under the Receiver Operating Characteristic Curve of0.94 [10].

III. Proposed Methodology

A. *The Dataset*

The High-Resolution Fundus (HRF) Image Database (benchmark dataset) consists of 1000 High Resolution Fundus Retinal Images out of which, 300 images are labelled as Healthyand 700 images are labelled as Diabetic [11]. Sample Images areshown in Fig 1.

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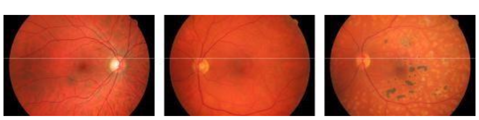

Fig. 1. Dataset Samples

B. *Data Pre-Processing*

Here Data is referred as High-Resolution Fundus RetinalImages.

1) 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.

2) Resizing: All the converted greyscale images are resized to a fixed size of 1000 x 1000 pixels.

3) 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.

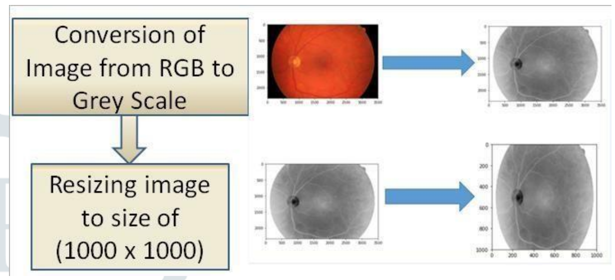

Fig 2. Image Transformations in Pre-Processing

C. *The CNN Architecture*

The deep-convolutional neural network architecture adopted is shown in Fig 10. The network contains an input layer which takes greyscale images of resolution 1000 x 1000 pixels as input. Then there comes 3-set-combination of Convolution. Each set consists of a Convolution Layer, a ReLU (Rectified Linear Unit) layer and a Max-Pooling Layer. The final set of feature maps (corresponding to a single image) obtained after the 3 sets are flattened or unrolled into asingle feature vector in the Flattening Layer. The single feature vector is then fed into an Artificial Neural Network which forms the Dense Layer of the Convolutional Neural Network.

1) Convolutional Layer: Convolution is a combined integration of two functions and it shows how one function modifies the shape of the other. (Fig 3) Each Convolutional Layer in all the 3 sets have 32 features detectors of dimensions, 3 x 3. Eachfeature detector is convoluted with the input image to generate convolved feature maps corresponding to every feature detector. A small example of a Convolutional Layer is described in Fig 3.

$$\begin{bmatrix} 0&0&0&0&0&0&0\\ 0&1&0&0&0&1&0\\ 0&0&0&0&0&0&0\\ 0&0&0&1&0&0&0\\ 0&1&0&0&0&1&0\\ 0&0&1&1&1&0&0\\ 0&0&0&0&0&0&0 \end{bmatrix} \otimes \begin{bmatrix} 0&0&1\\ 1&0&0\\ 0&1&1 \end{bmatrix} = \begin{bmatrix} 0&1&0&0&0\\ 0&1&1&1&0\\ 1&0&1&2&1\\ 1&4&2&1&0\\ 0&0&1&2&1 \end{bmatrix}$$

2)

Fig.3. Example of a Convolutional Layer

3) Max-Pooling Layer: Max-Pooling operation isdescribed in Fig 4.

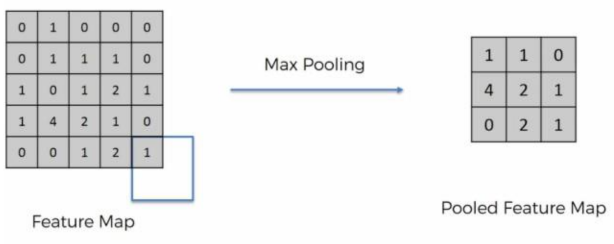

Fig.4. Max Pooling Layer

In each and every feature maps obtained in the ReLU Layer, Max Pooling is done where the pooling stride is of dimensions (2 x 2),to preserve the features and for making the Convolutional NeuralNetwork, spatial independent.

4) Flattening Layer: The final feature map, so obtained after the 3sets, is flattened or unrolled into a single feature vector in this layer as shown by taking an example in Fig 5.

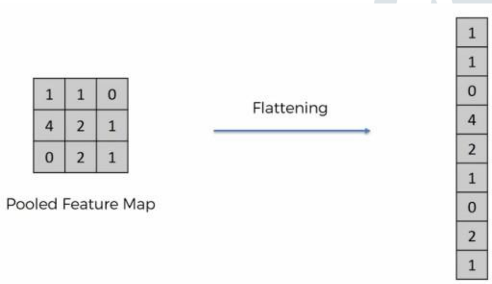

Fig 5.Flattening Layer

5) Dense Layer or Artificial Neural Network Architecture: The Artificial Neural Network or ANN consists of an input layer which takes a single feature vector as input. Then, it consists of a hidden layer containing 128 nodes to which the feature vector is forward propagated from the input layer by ReLU Activation. The following layer is the output layer which has a single node/unit that can assumevalues greater than or equal to zero but less than or equal to 1 as feature vector is forward propagated from the hidden layer to the output layer by Sigmoid Activation since it is a Binary Classification.If the output layer produces a value greater than 0.5, it is treated as Healthy but Diabetic otherwise. After the forward propagation steps, the whole Artificial Neural Network is back-propagated by taking Binary Cross Entropy Function as the loss function. For reducing theloss i.e., the value assumed by the loss function, Adam Optimizer is used with learning rate 0.00005.

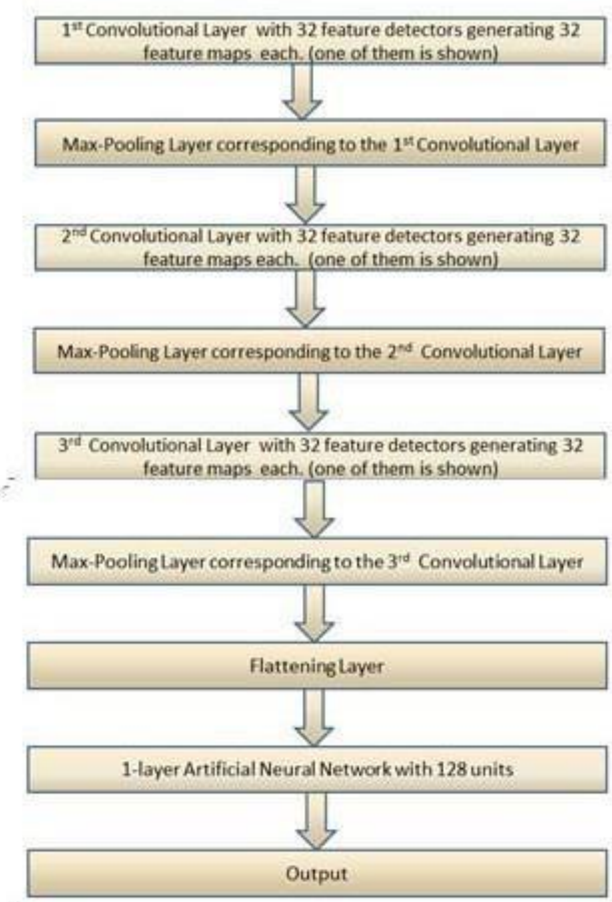

Fig. 6. The Schematic Diagram of CNN

IV. Training The Model

1000 images are chosen for training the model out of which 250 are labelled as Healthy and 650 are labelled as Diabetic. The remaining images, i.e. 100 images are chosen for validating the model, out of which 50 are labelled as Healthy and 50 are labelled as Diabetic. Then, all the images in the Training Set are augmented by creating different samples of the training images by zooming (zooming range=0.2). This is done as the dataset is quite small and Image Augmentation increases the number of training examples from existing samples for better performance of the CNN.

V. Details Of The Learning Process

In the learning process of the Deep Convolutional Neural Network, the Optimizer plays a pivotal role. The Optimizer used here is known as Adam Optimizer. It undergoes a mini-batch gradient descent where the batch size here, is set to 3 images per epoch or iteration. The number of epochs is set to28 and the Neural Network is made to learn.

Fig. 7. Proposed Deep Learning Approach

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_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_3 (Conv2D)            (None, 62, 62, 32)        896
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 31, 31, 32)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 29, 29, 64)        18496
_________________________________________________________________
global_average_pooling2d_2 ( (None, 64)                0
_________________________________________________________________
dense_3 (Dense)              (None, 128)               8320
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 129
=================================================================
Total params: 27,841
Trainable params: 27,841
Non-trainable params: 0
```

VI. IMPLEMENTATION DETAILS

The Data Pre-Processing is performed using Python on JupyterLab

The Convolutional Neural Network is trained on a machine with Intel(R) Core(TM) i5-4210U processor, CPU @ 1.70 GHz 2.40 GHz and 4 GB RAM. CPU is used as the interface with Python'sKeras Library (TensorFlow in the backend) and Python IDLE.

VII. RESULTS

- The Training Accuracy describes the accuracy achieved on the training set.
  From this model, a Training Accuracy of 78.3 %is achieved, which implies that 783 out of 1000 images were classified correctly whereas 217 images were misclassified.

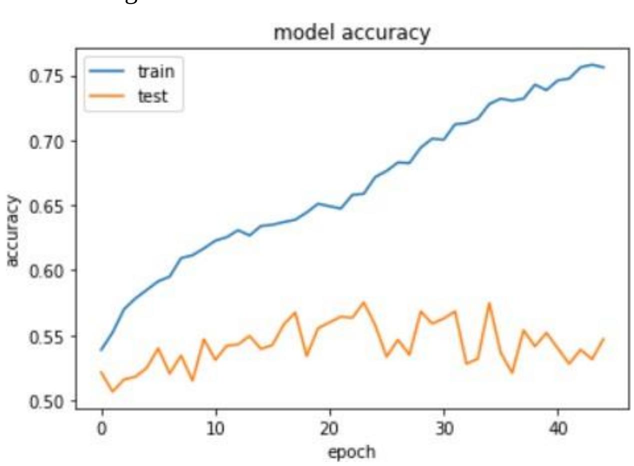

Fig. 8. Training and Validation Accuracy History (Accuracy vs Epoch)

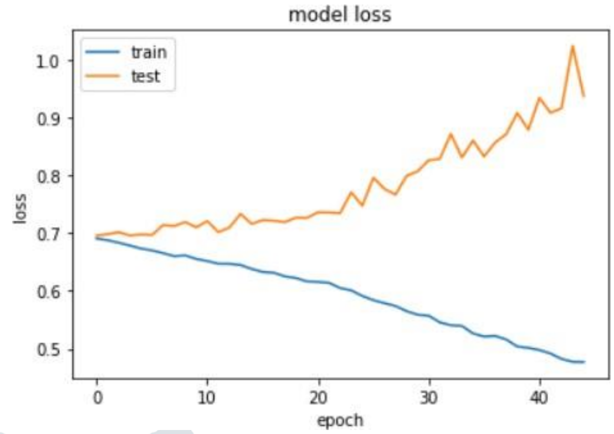

Fig. 9. Training and Validation Loss History (Loss vs Epoch)

CONCLUSION

This paper proposed a Deep Learning approachto Diabetic Retinopathy via Convolutional Neural Network and designing a typical CNN Architecture. Finally, a full 78.3 % Validation Accuracy is obtained which is, by far one of the best of our knowledge has been the highest ever numeric accuracy reached by any Automated Diabetic Retinopathy Detection Model. The research done in this paper is intended to help diabetic patients to remain cautious about their medical condition.

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