An Advanced Method of Detecting Diabetic Retinopathy Through Deep Learning

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Abstract- *Diabetic Retinopathy (DR) is a complication caused by diabetes that affects the human eye. It is caused by the mutilation of the blood vessels of the light-sensitive tissue at the back of the human retina. It's the most recurrent cause of blindness in the working-age group of people and is highly likely when diabetes is poorly controlled. Although, methods to detect Diabetic Retinopathy exist, they involve manual examination of the retinal image by an Ophthalmologist. The Proposed approach of DR detection aims to detect the complication in an automated manner using Deep Learning. The model is trained using a GPU on 35126 retinal images released publicly by eyePACS on the Kaggle website and achieved an accuracy of approximately 81%.*

Keywords- Convolutional Neural Network, Retinal Images, Deep Learning, Classification, Dropout, Max Pooling.

I. INTRODUCTION

Diabetic Retinopathy (DR) is an eye disease affecting the human retina. The blood vessels in the retina swell up which result in its rupture which in turn leads to blindness. The initial stages of DR are characterized just by swelling and the final stage by rupturing of blood vessels. The symptoms in the advanced stage are not easily observable therefore if detected early, may assist in the prevention of vision impairment. The existing process to screen DR is time-consuming and is hampered by the lack of trained ophthalmologists. It involves dilating the eye to widen the pupil, performing fluorescein angiography, using a special camera to capture an image of the retina and examination by the clinician. It has been approximated that in 2002 diabetic retinopathy has resulted in about 5% of the world blindness, constituting nearly 5 million people. Moreover, in rural regions where the number of diabetic patients is comparatively high, the wanting of trained clinicians poses a huge problem. Diabetic Retinopathy is classified into 5 stages (shown in Fig. 1.) which are No DR, Mild Non-Proliferative DR (NPDR), Moderate Non-Proliferative DR, Severe Non-Proliferative DR and Proliferative DR. Mild Non-Proliferative DR is very difficult to detect as the symptoms include slowing of retinal blood flow, increased leukocytes adhesion and loss of retinal pericytes. Moderate NPDR is marked by the development of Microaneurysms. This stage also shows venous calibre changes and intra-retinal microvascular abnormalities. In Severe NPDR, blood vessels swell up to a stage where blood supply within them is severely affected. These damaged blood vessels then get replaced by new blood vessels. In Proliferative DR these new fragile blood vessels rupture rapidly leading to permanent blindness.

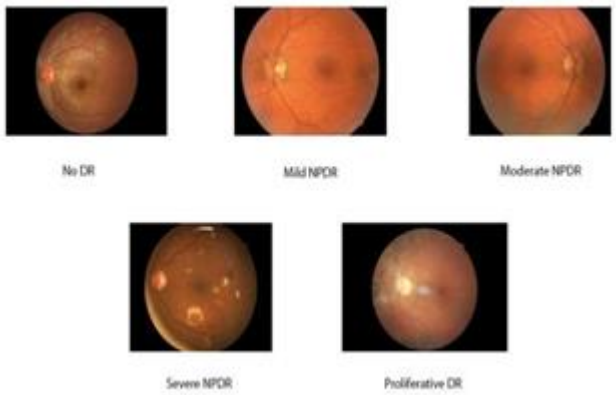

Fig. 1. Diabetic Retinopathy Stages

II. RELATED WORK

Researchers have been working on methods to automate the process of DR detection. Enrique Carrera et al [1] in their paper proposed a technique based on SVM to help diagnose diabetic retinopathy in advance. In this approach, an initial pre- processing stage segregates the blood vessels, microaneurysms and hard exudates to extract features to be used with SVM. The model tested on the STARE dataset resulted in a sensitivity of 94.6%. The implementation proposed by Mohamed Chetoui et al [2] has introduced the use of Local Energy based Shape Histogram (LESH) and Local Ternary Pattern (LTP) which outperforms the LBP extracted features. This model achieved an accuracy of 90.4% on MESSIDOR database which contains 1200 images. Martina Melinscak et al [3] implemented a deep convolutional neural network to segment blood vessels. The model was made up of

10 layers which achieved an accuracy of 94% on the publicly available DRIVE dataset. Satish Kumar et al [4] in their paper proposed a DR detection technique based on a linear support vector machine. They extract the number of microaneurysm from the colour fun- dus image. Microaneurysms are localised capillary dilatations which are usually saccular (round). They appear as small red dots on the retina, shaped by engorging fragile part of blood vessels. Using the DIARETDB1 database their system could achieve 96% and 92% sensitivity and specificity respectively. Manisha Manjramkar [5] in her survey of various diabetic retinopathy detection techniques such as KNN, Adaboost, and SVM resulted in an accuracy of 68.7 to 98.1 on the DRIVE, Messidor and DIARETDB1 dataset. Karan Bhatia et al [6] have proposed a paper that used Alternating decision trees, AdaBoost, Naive Bayes, Random Forest, and SVM. The main features under consideration were the diameter of the optic disk, lesion-specific (exudates, microaneurysms), image-level (prescreening, AM/FM, quality assessment). They were able to achieve an accuracy of 88% on the Messidor dataset. Anaswara Chandran et al [7] extracted the vessel maps using the Gabor wavelet transform. These vessel maps are then given as input to the Random Forest Classifier. Random Forest Classifier was used due to its capability of handling higher dimensional feature sets. They achieved an accuracy of 90% on the MESSISOR and STARE dataset. Saket Kanth et al [8] used Multilayer Perceptron (MLP) with Back Propagation with consideration of important features such as area of 'on' pixels, mean and area of exudates. They collected 150 fundus images from hospitals in Noida and Delhi in India. They achieved an accuracy of 94.11%. K. K. Palavalasa et al [9] in their study used Contrast Limited Adaptive Histogram Equalization (CLAHE) technique to intensify the contrast of the image and Recursive Region Growing Algorithm (RRGA) for detection of larger exudates. On the DIARETDB1 dataset, they achieved a sensitivity of 87%, F-score of 78% and Positive Predict Value of 76%. In their paper, A. Herliana et al [10] applied the particle swarm optimization (PSO) technique to determine the best Diabetic Retinopathy feature from the dataset images. The selected attribute is further characterized using Artificial Neural Network. Dataset was partitioned into 10 parts and 10-fold cross-validation is employed. The performance was recorded for Neural Network + Particle Swarm Optimization model and accuracy was observed to be 76.11%. Z. A. Omar et al [11] proposed an Automated DR detection system based on vessel and haemorrhages detection, optic disc removal and exudate detection. They trained the model using training data obtained from Hospital Serdang, Malaysia and tested it on the DIARETDB1 dataset. They achieved an accuracy of 80.65% for Vessels and haemorrhages detection and 86.21% for Exudates.

III. DATASET

A. Overview

The dataset used is provided by EyePACS and is freely available to download from Kaggle.com [12]. All images are taken of different people, using different cameras, and of different sizes.

B. Biased Data

The dataset contains 35126 images. Images in the dataset are highly imbalanced which will make the model very diffi- cult to train. Images belonging to class 0 which is No DR make up 73.47% of the entire dataset hence, data augmentation is used to balance the classes. Data augmentation is the process of extrapolating the dataset(increasing the count) by using existing data. TABLE I shows the exact number of images belonging to each class.

TABLE I BIASED DATA

Class	Count
No DR	25810
Mild NPDR	2443
Moderate NPDR	5292
Severe NPDR	873
Proliferative	708

IV. METHODOLOGY

A. Pre-processing

This data is very noisy, hence multiple preprocessing steps were applied to get all images in a format suitable for train- ing. Preprocessing includes cropping, resizing and removal of black images. Images are of size around 4000x3200 and cropping is done to remove the black surroundings and get the centre of the retinal image. The images are resized to 256x256 pixels as shown in Fig. 2. to bring the images to a standardized form and reduce the number of data points. Some images of the dataset are completely blacked out and hence, need to be removed. This is done by taking the arithmetic mean of all pixels and comparing it with zero. If the mean is zero, the image is black and hence dropped.

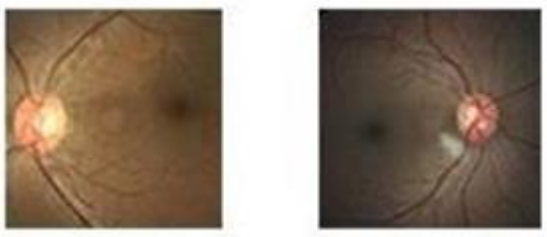

Fig. 2. Images resized to 256x256

B. Data Augmentation

The dataset contains 25810 No DR images and 9316 DR images which can lead to a class imbalance problem. Conse- quently, the model would be biased towards the No DR class. To resolve this problem, images of any DR level are mirrored and rotated by 180 degrees. This augmentation step would result in a total of 27948 images with DR thus increasing the dataset size from 35126 to 53758. The figure below shows the original, mirrored and rotated image.

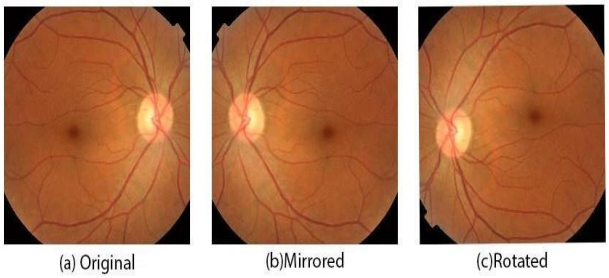

Fig. 3. Original, Mirrored & Rotated Image

C. Convolutional Neural Network for Image Recognition

Convolutional Neural Networks are a type of Neural Net-work which are particularly designed to work with Image Recognition applications. Like Neural Networks, CNNs are constructed using neurons with weights and biases. Every neuron receives multiple inputs, gets a weighted sum over them, course it through an activation function and responds with the resulting output. CNNs work better because they have filters that act like "feature detectors" that somewhat mimic the human visual system. CNN contains an input layer, an output layer, and several hidden layers. The hidden layers typically include Fully Connected Layers, Convolution layers, Pooling layers, Activation Layers. A representational diagram of CNN is given in Fig. 4.

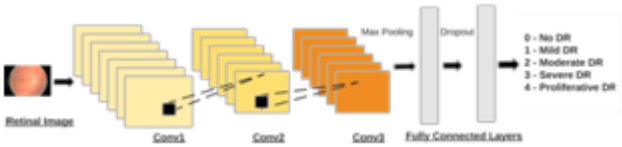

Fig. 4. Convolutional Neural Network

1) Convolution Layer: The convolution layer is the heart of a Convolutional neural network. It applies a filter on the input before passing it to the next layer. The filter acts as "visual stimuli" and emulates the human visual sensory system. Although fully connected neural networks can be used to learn features as well as for the classification of data, it's not a pragmatic approach to apply this architecture to images. A large number of neurons would be required due to the enormous input sizes of the images, where each pixel can contribute as a relevant variable. The convolution layer makes use of kernels or a set of filters. During a forward iteration, each filter (or kernel) is convolved across the entire input image finding a dot product between the filter and chunks of images. For every dot product taken, the result is a scalar. So, if the input is of size NxN and filter of size mxm, the convolution layer result will be of size (N-m+1) x (N-m+1).
2) Pooling Layer: A pooling layer is another building block of the convolution neural network. Its function is to reduce the number of parameters and computation in the network by reducing the structural size of the representation. Here, filters are applied on the input which is typical of size 2x2. Pooling may evaluate the max or average. In max pooling, the maximum value of the neurons from previous layers is used and on average pooling, the arithmetic mean is used.
3) Fully Connected Layer: A fully connected layer (FCL) is essentially similar to a multi-layer perceptron neural net-work. In FCL, every neuron of the same layer is connected to every other neural in another layer. CNNs can consist of one or more fully connected layers. The flattened matrix is fed to the FCL to classify the images.
4) Dropout Layer: Dropout is a simple technique that helps prevent overfitting of the neural network. Some randomly selected neurons are not updated during a training pass i.e. they are 'dropped out'. No weight update is done on those selected neurons. As a result, the network becomes less sensitive to the specific weights of a neuron providing better generalization capability.
5) Classification Layer: The final layer which comes after all the other layers is the network and outputs the classification of the input image.

Several CNN architectures have been proposed and tested in our experiments. Fig. 5. contains a summary of the CNN archi- tecture used in our experiment. The input size is 256x256x3. On giving an input retinal image, the network outputs the prediction of the image.

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 253, 253, 32)	1568
conv2d_2 (Conv2D)	(None, 250, 250, 32)	16416
max_pooling2d_1 (MaxPooling2	(None, 31, 31, 32)	0
flatten_1 (Flatten)	(None, 30752)	0
dense_1 (Dense)	(None, 2048)	62982144
dropout_1 (Dropout)	(None, 2048)	0
dense_2 (Dense)	(None, 2048)	4196352
dropout_2 (Dropout)	(None, 2048)	0
dense_3 (Dense)	(None, 5)	10245

Total params: 67,206,725
Trainable params: 67,206,725
Non-trainable params: 0

Fig. 5. Model Summary

V. EXPERIMENT RESULTS

The experimental setup includes a Google Cloud Instance having 12 vCPUs, Nvidia Tesla T4 GPU and 128GB ram. The model presented was developed using Keras with TensorFlow backend for Python.

A. Evaluation Metrics

On the fact that this is a medical-related classification problem and the inherent class imbalance, accuracy won't be an appropriate evaluation measure for the model. Instead, sensitivity and precision will be used. Four parameters required for these calculations are True Positive (TP) = No. of inputs which have been correctly classified as positive, True Negative (TN) = No. of inputs which have been correctly classified as negative, False Positive (FP) = No. of inputs which have been classified as positive but are negative, False Negative (FN) = No. of inputs which have been classified as negative but are positive. Sensitivity (or Recall) is defined as the proportion of the cases that are actually positive and that also got predicted as positive (or true positive). Mathematically, sensitivity can be calculated as Sensitivity = (TP) / (TP + FN). Specificity is described as the positive cases that are negative and which also got predicted as the negative (or true negative). Mathematically, the specificity is computed as the following: Specificity = (TN) / (TN + F). Accuracy (AC) is given by the percentage of the total number of prophecies that were correct and is given by, Accuracy = (TP + TN) / (TP + TN + FP + FN). Precision is the proportion of total positive predictions that are actually correct. Precision = (TP) / (TP + FP).

B. Performance

The dataset was split in 9:1 ratio where 9 parts were used for training and 1 part for testing. Therefore, 10% of the data was used for validation. From the confusion matrix shown in TABLE II, we can observe that relatively high images of class 1(Mild) and class 2(Moderate) are classified incorrectly as class 0 (Non-DR). The model attained an accuracy of around 81%. Precision and recall for each class are given in TABLE III.

TABLE II CONFUSION MATRIX

	0	1	2	3	4
0	2375	125	24	48	9
1	226	270	93	142	2
2	248	304	773	185	77
3	2	21	51	151	37
4	3	17	29	62	101

TABLE III PRECISION AND RECALL

Class	Precision	Recall
0	0.832	0.92
1	0.366	0.368
2	0.796	0.462
3	0.256	0.576
4	0.447	0.476

VI. CONCLUSIONS

With the limited availability of clinicians for manual de- tection of DR, an automated approach can greatly reduce the manual labour required for diagnosis. The model presented classifies the retinal images using Deep CNN which relies less on manual feature extraction thus providing a wholesome approach to DR detection. The model is evaluated with various metrics and considering the complexity of the dataset the model is satisfactory. Accuracy can be further improved by augmenting the dataset even more and by retraining the neural network with new retinal images. This is a widely used practice and helps improve the model. Although at this level the system may not gain the confidence of affected patients, further improvement can act as a boon for both the doctors and the patients. Patients can rely on the system for proper diagnosis and doctors can rely on the system for reducing their heavy workload.

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