Detection of Diabetic Retinopathy using Convolutional Neural Network

Razat Agarwal, Aditya Mahamuni, Noopur Gautam, Piyush Awachar, Parth Sagar

Abstract*: Diabetic Retinopathy is a medical condition in which damage occurs to the retina due to diabetes mellitus. The diagnosis of Diabetic Retinopathy through colored fundus images stand in need of experienced clinicians to identify the presence and significance of many small features, which makes it a time consuming task. In this paper, we propose a CNN based approach to detect Diabetic Retinopathy in fundus images. Data used to train the model is prepocessed by a new segmentation technique using Gabor filters. Due to small dataset, data augmentation is done to get enough data to train the model. Our segmentation model detects intricate features in the fundus images and detect the presence of DR. A high-end Graphics Processor Unit (GPU) is used to train the model efficiently. The publicly available Kaggle Dataset is used to demonstrate impressive results, particularly for a high-level classification task. On the training dataset of 14,650 images, our proposed CNN achieves a specificity of 94% and an accuracy of 69% on 3,660 validation images.

Index Terms: Augmentation, CNN, Fundus, Segmentation.

I. INTRODUCTION

Diabetic Retinopathy is an eye complication, which is found in diabetic patients. The main cause of DR is damaged blood vessels in the retina, a light-sensitive tissue. Patients suffering from Type 1 or Type 2 diabetes are more prone to this complication. The chances of this complication being present in the eye increases if the patient has a prolonging case of diabetes and the blood sugar level is not controlled systematically.

In the western world, one of the principal causes of blindness is found to be Diabetic Retinopathy. Prevailing monitoring, of the patients suffering from diabetes, of Diabetic Retinopathy is found to be of great use for its prevention. Due to the availability of treatment for Diabetic Retinopathy, this process is found to be essential if this condition is detected in its early stages.

Millions of people suffer from Diabetic Retinopathy, the leading cause of blindness among working aged adults. Aravind Eye Hospital in India hopes to detect and prevent this disease among people living in rural areas where medical screening is difficult to conduct.

The weighting of numerous features and the location of such features are highly involved in the classification of Diabetic Retinopathy. The task when done by clinicians in highly time consuming. To give the clinicians the ability to aid in real-time, Computers are used to make quicker classification if trained correctly. The efficacy of automated grading for Diabetic Retinopathy has been an active area of research in computer imaging with encouraging conclusions[1],[2].

Convolutional Neural Networks (CNNs), a branch of deep learning, have an impressive record for applications in image analysis and interpretation, including medical imaging. Network architectures designed to work with image data were routinely built already in 1970s with useful applications and surpassed other approaches to challenging tasks like handwritten character recognition. However, it was not until several breakthroughs in neural networks such as the implementation of dropout, rectified linear units and the accompanying increase in computing power through graphical processor units (GPUs) that they became viable for more complex image recognition problems. Presently, large CNNs are used to successfully tackle highly complex image recognition tasks with many object classes to an impressive standard. CNNs are used in many current state-of-the-art image classification tasks such as the annual ImageNet and COCO challenges.

In this paper, we propose a deep learning-based CNN approach to detect Diabetic Retinopathy in fundus images. We also developed a new segmentation process for blood vessel segmentation for better training of the model. This being a diagnostically relevant medical imaging task, has been a topic of discussion in earlier studies. To compensate the low number of images in the training dataset, Image Augmentation methods is applied on the images to increase the dataset. More number of images led to better training results as well.

II. RELATED DATA

The data used in this research paper has been collected from APTOS 2019 Blindness Detection Competition hosted on Kaggle. The data available has 3,662 RGB images comprising of fundus images labeled according to five level of DR classification. The image is pre-processed to train the model faster.

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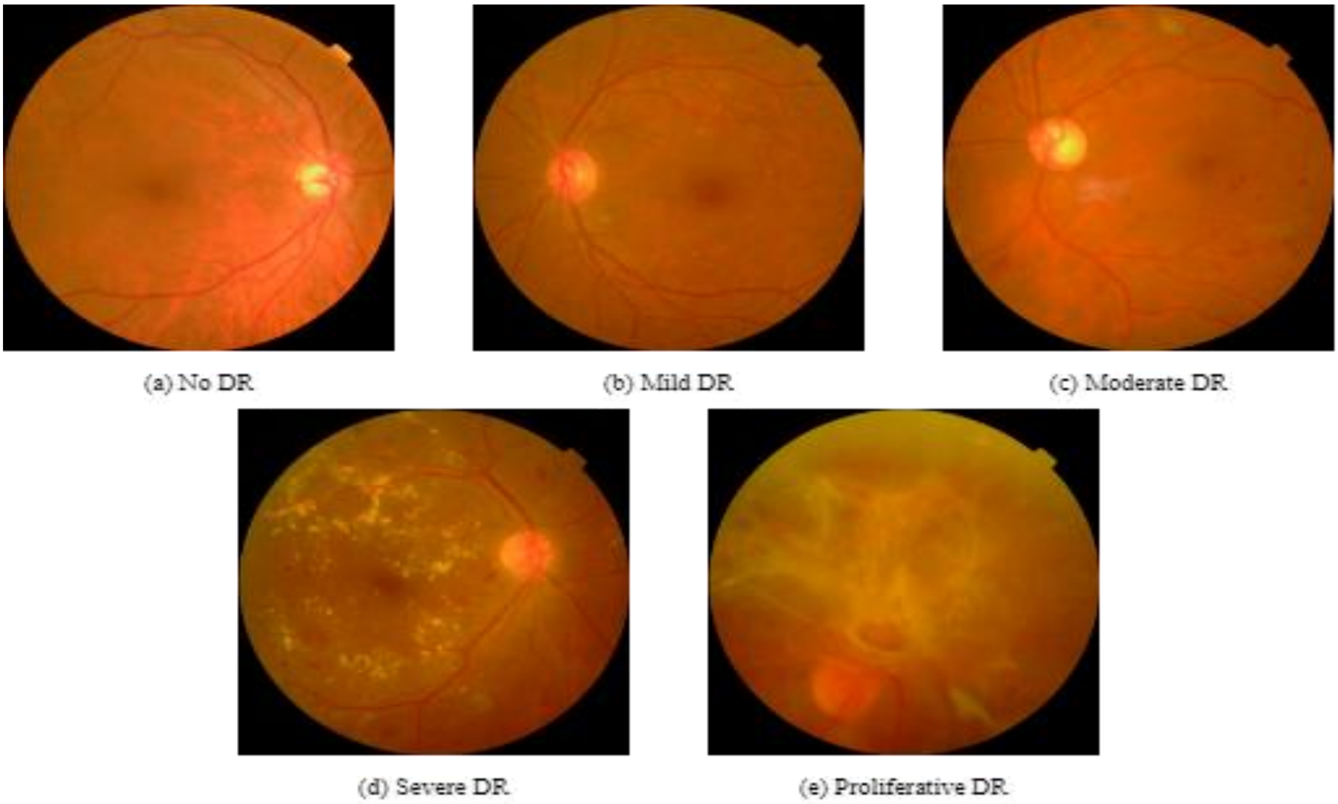

Fig. 1. Stages of diabetic retinopathy (DR) with increasing severity

The preprocessing stage consists of data segmentation for highlighting the blood vessel in the fundus images. The data is not enough hence, the data is augmented to increase the size of the dataset. The data is divided into two sets, 2,930 images in the training set and 732 images in the validation set.

III. PROPOSED METHODOLOGY

The proposed architecture for the implemented work mainly consists of five steps: Loading the data, Segmentation of the image, Augmentation of data, Training of the Model and Saving the model.

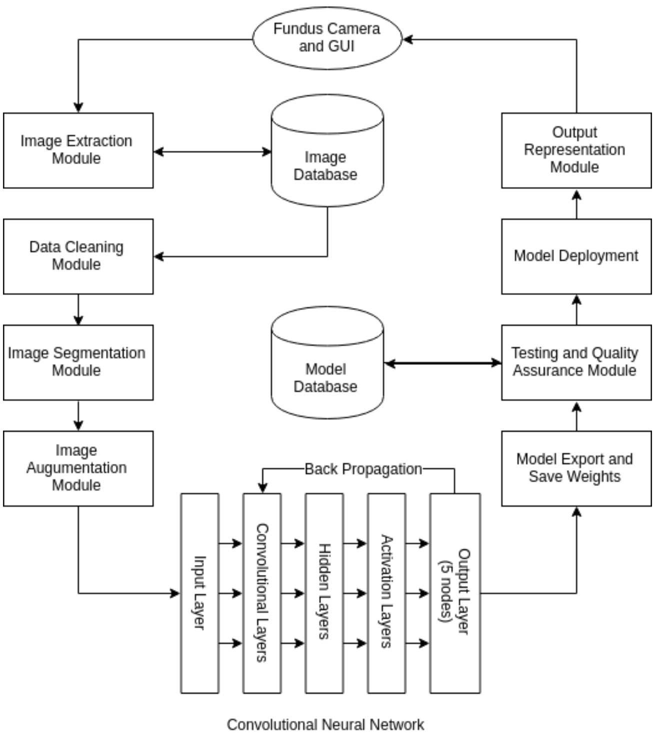

Fig 2. System Architecture

A. Loading the Data

The dataset used is provided by Kaggle and consist a total 3,662 fundus images. To train and evaluate the model, the dataset is divided into Training Set, 2,930 images, and Validation Set, 732 images.

The images are classified into five categories, the categorical classification is given in Table-I.

Table-I: Classification of data

S. No.	Name of the class	No. of Images
1	No DR	1,805
2	Mild DR	370
3	Moderate DR	999
4	Severe DR	193
5	Proliferative DR	295

B. Segmentation

The blood vessels has been acknowledged as a very important aspect in determining Diabetic Retinopathy in the retina. Segmentation of the retinal vessel tree is a prerequisite for computer aided diagnosis system. For enhancing the blood vessel structure in the retina, we use a segmentation module. The segmentation module is used to highlight the blood vessels in the retina and improves the accuracy of the model. Segmentation is a very important step in any image classification task and always help in the better training and classification of any image classification model.

In previous works, the blood vessel segmentation in the retina is done by U-NET, a type of Convolutional Neural Network[3].

This type of network cannot be implemented in this research as the CNN requires segmented images of the retina for training, which is not available in this dataset, and manually segmenting the image is a tedious task.

Another proposed work is a fully convolutional AlexNet for retinal vessel segmentation [4]. This type of network also proposed to work on the STARE dataset, which consists of previously segmented training data.

An ensemble classification based approach is also proposed to be applied for Retinal Blood Vessel Segmentation [5].

As there is a lack of segmentation module in the previous works for the classification of DR using this dataset, we propose a new architecture for segmentation of the blood vessel in the retina captured by the fundus images. In our research, we use a combination of transformations and filters to achieve a good enough segmentation to train the model.

Following steps are applied in the segmentation module, the results of which can be seen in Fig. 3:

1) Convert image to grayscale: The original image obtained is 3D in nature. To decrease the complexity we convert the image into grayscale which results in the image to be 1 dimensional.

2) Apply top-hat transformation: Top-hat transformation is an operation that extracts small elements and details from the given image. The white top-hat transformation of f is given by:

$$T_w(f) = f - f \circ b$$

Where $\circ$ denotes the opening operation.

3) Apply Gabor filtering: To detect specific frequency pixels in an image, Gabor Filters are used. Mainly Gabor filters is used for texture analysis in images [6].

4) Apply Thresholding: To create binary pixels, thresholding is used. A certain value of threshold is set according to which the threshold is applied. Thresholding is used to convert grayscale images into binary images.

5) Apply Opening Morphological Transformations: To remove the noise in the final image, this transformation is applied. Opening Morphological Transformation is just erosion followed by dilation.

All the above transformations are done using the Open Source Computer Vision Library (CV2) in Python.

C. Augmentation

The original pre-processed images are not enough to train the model very thoroughly. To increase the number or images, Augmentation techniques are applied to all the images such as rotation, zoom, horizontal flip, vertical flip, blurring, brightness and saturation. All the parameter values were randomly generated and applied using ImageDataGenerator in Keras Preprocessing Library.

The data is augmented and the resulting dataset consists of 14,650 images in the training dataset and 3,660 images in the validation dataset.

D. Training the model

After studying different structures of CNN we applied the architecture of multiclass InceptionV3 for our training. Increased convolutional layers boost the ability of learning deeper features in our neural network.

InceptionV3 is a widely-used image recognition model that has been shown to attain high accuracy on the ImageNet dataset[7]. The network is 48 layers deep and uses softmax activation function to predict our classification. The learning rate is kept as 0.0005 and batch normalization has been used.

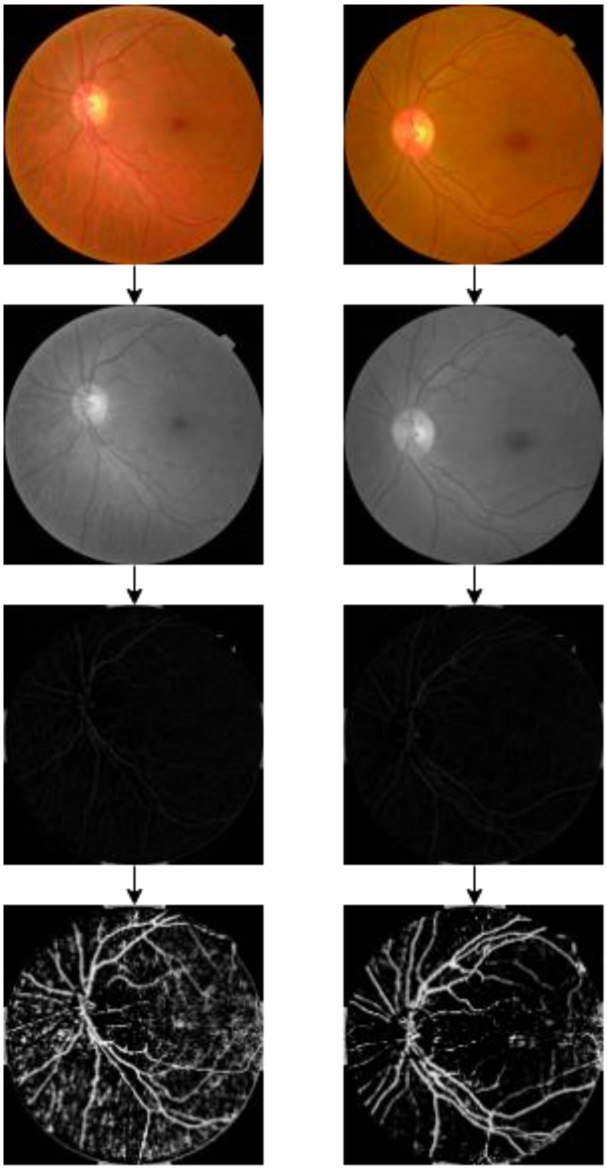

Fig 3: Segmentation applied on two images

The network is also initialized with Gaussian initialization to reduce initial training time. The network is trained for 200 epochs to get the documented accuracy.

IV. RESULTS

3,660 images from the dataset were saved for validation purposes. Running the validation images on the network took 152 seconds. In this classification problem, specificity is defined as the number of images which are predicted as not having DR correctly in association with the total number of images not having DR. Accuracy is defined as the total number of images on which DR is detected correctly in association with the total number of images. Specificity of 94% and Accuracy of 69% is achieved on the final neural network. The classification in the network were defined numerically as : 0 – No DR, 1 – Mild DR, 2 – Moderate DR, 3 – Severe DR and 4 – Proliferative DR.

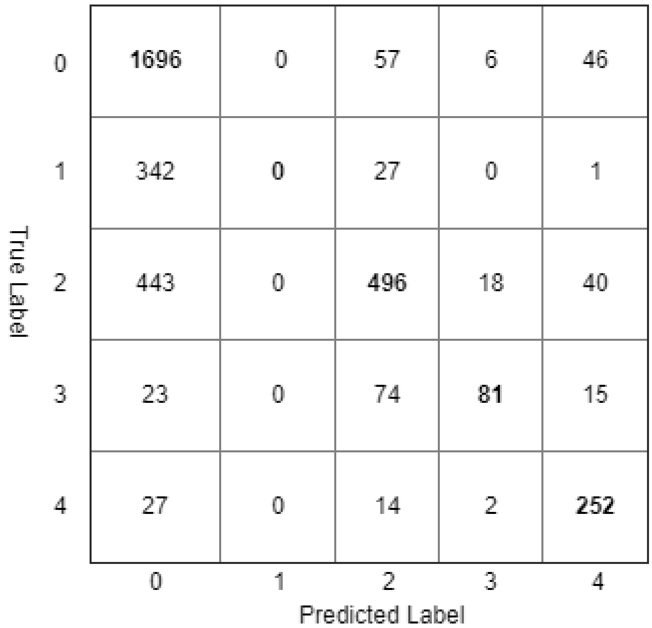

Fig. 4: Confusion Matrix of final classification results

V. DISCUSSION AND CONCLUSION

The majority of images classified as proliferative DR are detected accurately by our neural network. To classify the fundus images, encouraging signs are shown by our network in learning the features required. A trade off between lower sensitivity and higher specificity is observed in other studies including large datasets[8].

In future, we have plans to test other image classification models. We will also try another blood vessel segmentation techniques which can lead to better results. If possible then we will also try to gather more images to train the model on a better dataset.

To conclude, we have shown that CNNs can be trained to detect Diabetic Retinopathy in fundus images. Ophthalmologist can use CNNs for a second opinion in the classification problem.

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