Detection and Classification of Diabetic Retinopathy using Deep Learning

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***Abstract*— The most common reason for blindness in adults in developed nations is Diabetic Retinopathy(DR). Currently, diagnosing DR involves an in-depth arduous examination of digital colour fundus pictures of the retina by a qualified practitioner. By looking for lesions connected to the vascular anomalies brought on by the illness, ophthalmologist can recognise diabetic retinopathy. Although this strategy works, it has substantial resource requirements. It has long been understood that a thorough and automated approach of detecting diabetic retinopathy is necessary, and prior initiatives have achieved excellent strides utilising image classification, pattern recognition, and machine learning.**

This project seeks for automated detection, grading, and segmentation of Diabetic Retinopathy. In our project we aim to improve image segmentation using UNet and to automise the project using Convolutional Neural Networks and VGG16.

Keywords: Diabetic Retinopathy, detection, segmentation, UNet, Convolutional Neural Networks, VGG16.

I. INTRODUCTION

Diabetes mellitus or more commonly known as ‘diabetes’ is a form of metabolic disease which happens due to high blood sugar levels in your body. It is a very common disease in India though it is a highly dangerous disease, India has the 2nd largest population of diabetics followed by China. In many of the diabetes patients over time, a certain eye condition known as Diabetic Retinopathy is developed which causes gradual vision loss over time. It affects blood vessels in the retina which can be detected via examining images of the retina. Since diabetes is a very common disease among Indians, it becomes highly important that there should be regular checkups for diabetic retinopathy (DR).

Right now, the evaluation of images may remain a complex task, but the advancing field of machine learning in computer vision can be utilized to diagnose the extent of infection. It can be used to train the model efficiently using deep learning frameworks and can use to detect the level of damage done to the eye by DR. There are four stages through which Diabetic retinopathy usually progresses:

1. Mild non-proliferative retinopathy, the initial starting stage of DR is the occurrence of microaneurysms (MA).
2. In moderate non-proliferative case of retinopathy, the arteries and veins of the retina start losing their ability to transport the blood.
3. In severe non-proliferative retinopathy, the retina's blood supply is depleted as a result of an increase in blood channel blockages, which leads the retina to emanate new blood vessels.
4. The most advanced stage of diabetic retinopathy is called proliferative diabetic retinopathy (PDR). In this stage, the retina's growth factors stimulate the growth of new blood vessels that are weak and frequently bleed and leak. They also grow inside the retina's covering, resulting in vitreous gel that fills the eye. A retinal detachment caused by the accompanying scar tissue might result in irreversible visual loss.

The subject of diabetic retinopathy has previously been the subject of much study in both medical sciences and as well as in machine learning the related work in these fields, demonstrates that many machine learning techniques have been developed and used by researchers, but there hasn't been a thorough comparison of these deep learning techniques for treating diabetic retinopathy.

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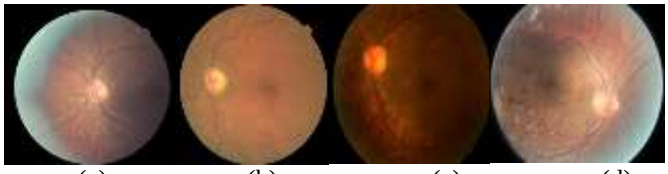


(a) (b) (c) (d)

Fig 1: (a) Mild non-proliferative retinopathy (b) Moderate non-proliferative retinopathy (c) Severe non-proliferative retinopathy (d) Proliferative diabetic retinopathy

II. LITERATURE SURVEY

Many studies have been conducted on DR classification. (Casanova et al. 2020) used Random Forests to find the impact of sample size on classifier performance and the possibility of using Random forest generated class conditional probabilities as metrics describing DR risk. They find that RF-based models produce much higher classification accuracy than those based on logistic regression. Combining both types of data did not result in accuracy improvement but did increase statistical discrimination of healthy participants who subsequently did or did not have DR events during four years of follow-up.

In Automatic Recognition of Microaneurysms in Diabetic Retinopathy by Lay et.al, 2021 (FA), the paper involves morphological openings with linear structuring elements in different directions. This removes MA but preserves the piecewise linear vessels. Such image is subtracted from original image (top-hat transformation) to extracts MA details.

(Das et al. 2022) [7] aims to create a screening tool that automatically scans digital colour retinal pictures for indicators of non-proliferative diabetic retinopathy.. Their designed algorithm was able to detect hard exudates. This provides an inspiration of feature extraction about this topic.

Then, in (Usher et al. 2019), the authors develop a system to automatically detect features of DR in color digital retinal images and evaluate the potential of those features in DR screening. They draw the conclusion that at 94.8% With the development of deep learning techniques, some papers have applied several deep-learning models to tackle this problem. Specifically, convolutional neural networks have been applied for automated, quick and precise identification of the disease.

Authors have previously applied deep learning techniques to improve the accuracy as well as the sensitivity of this problem. For instance, (L. Qiao et al. 2020) [4] compares the performance of an automated deep learning algorithm compare with manual grading by ophthalmologists for identifying DR. They found that in 2 validation sets of 9963 images and 1748 images separately.

A separate research (S. Jyotheeswar et al. 2022) [9] analyses the effectiveness of a deep-learning augmented method for automated identification of DR using a different criterion.

For their evaluation of the model, they employ the previously published agreed reference standard of referable DR, as well as estimated negative predictive value, area under the curve, and confidence intervals.

They discover that an algorithm for this problem that has been modified by deep learning would perform noticeably better than what has previously been reported when utilising conventional machine learning methods. In the year 2021, R. S. Rajkumar et al and D. Ragul, Venkatesh Pagidimarri et al [6], also used deep convolutional neural networks to challenge the problem. Thus, utilising colour fundus pictures and deep convolutional neural network methods, they investigated the automated categorization of diabetic retinopathy in this research. On our dataset, R. S. Rajkumar et al. achieved an accuracy of 93.2%, exceeding the outcomes attained using conventional methods. Additionally, Manoj Raju, Venkatesh Pagidimarri, et al. trained the network using about 34,540 photos. On the validation dataset of about 54,750 photos, they attained a responsivity of 81.38%, distinction of 92.29%, and precision of 93.28%.

In our paper, we add to the growing base of knowledge of deep learning methods in medical imaging.

IV. DATASET:

Data for this experiment was drawn from a dataset provided via Kaggle.

The details of the ones used are given below:

1. DRIVE: The Digital Retinal Images for Vessel Extraction (DRIVE) dataset. This dataset co of 40 fundus images, all with a resolution of 584 × 565, with eight bits per colour channel (3 channels). These images were arbitrarily selected from a screening variety of about flemish contributors suffering from the disease. In this set of 40 fundus images, 33 of them are supposed to be healthy, and the rest 7 had early symptoms of diabetic retinopathy.
2. We collected over 200 fundus images of the eye from several local hospitals in our city. Out of the 200 fundus images acquired, 30 had proliferative diabetic retinopathy, 27 had severe case of the disease, 15 had moderate symptoms and the rest had mild to none diabetic retinopathy.
3. STARE: The STARE dataset has images from the Structured Analysis of the Retina project. It contains 20 equal-sized (700×605) colour fundus images.

V. METHODOLOGY

A. IMAGE SEGMENTATION:

Vessel segmentation and artery classification are the essential steps in automated retinal image processing and offer a variety of information about probable problems. Efficient Artery and Vein segmentation systems are of great importance. Steps used in Image Segmentation:

1. Image Augmentation
2. Image enhancement/pre-processing
3. Training a U-Net model
4. Checking the performance of the model on the Validation

Dataset Image Augmentation: Since we were using DRIVE dataset for image segmentation, we had only 20 images, in the training dataset, thus we used many data augmentation techniques, like horizontal flipping, vertical flipping, rotations of the images at angles of 90 and 270 degrees. Below is an example of augmented image:

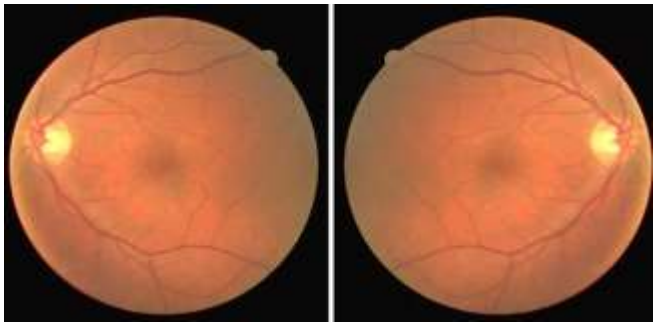
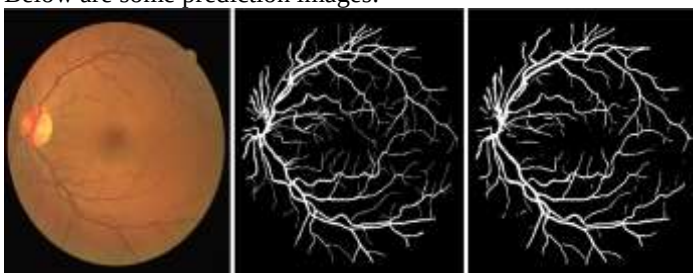


Fig 2: Original image Horizontal filp applied

Image Enhancement/Preprocessing: As we know that Retinal fundus images suffer brightness issues and also the contrast between the vessels and the background is pretty low, we applied local contrast enhancement, Contrast Limited Adaptive Histogram Equalization to the images(CLAHE). Also, we used to green channel of the images for training our model, as it has the most contrast between the background and the vessels. We also used gamma correction in the images, with the gamma value = 1.2 as it was giving the best results. Training the U-Net model While Training the model we have used a model similar to the one shown in the U-net Architecture image[3]. We have used valid convolutions of 3*3 kernels in between layers, and Max Pooling layers of size 2*2 of stride=2. We trained the model for 20 epochs, as our local system was unable to handle a load greater than 20 epochs. 7 Checking the performance of the model on the Validation Dataset After Training the model and checking the performance on the validation dataset, we obtained the following scores:

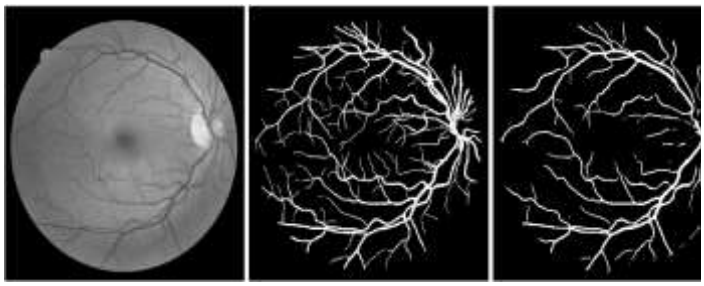
Accuracy: 94.46% IOU score: 60.79%

Below are some prediction images:



(a) (b) (c)

Fig 3 : (a) Original Image (b)Original Mask (c)Prediction



(a) (b) (c)

Fig4:(a)Original Greyscale Image (b)Original mask (c)Prediction (Green Channel)

As we can see, the narrow vessels are not being segmented, thus we need to run our training for more number of epochs, and also work on using some better enhancement/pre-processing techniques in our image to get better results.

B. MODEL

For training the preprocessed images deep learning models are used. The models used their accuracy compared to find the optimal model which correctly predicted the corresponding labels for each image.

A powerful open-source software library, Keras was used to build these models. Keras provides a python interface for artificial neural networks it supports multiple backends such as TensorFlow (also used to build our models, Keras have acted as an interface to it), Microsoft Cognitive Toolkit, Theano, and PlaidML, all these libraries are again used for building up artificial neural networks such as multilayer NNs, CNNs

Model 1: Single channel 2-dimensional Sequential 2-layer convolutional neural network:

The size of the input array used in this model is (3662, 224,224,1). Every convolutional layer has 3x3 kernel size and 32 units is for first layer and then there is 64 units in CNN for next layer. Max Pooling is done after layer to reduce the extent of features being lost along with padding, for every layer RELU activation is applied at the end there is a dense layer where the output is computed and which has 5 neurons (corresponding to 5 class labels), SOFTMAX activation function has been used. Also, a dropout layer has also been added to add dropout to the input. The model is compiled using the 'Categorical Crossentropy' function for computing the loss, Adam optimizer is used and accuracy metrics is used.

Model 2: Three channel 2-dimensional Sequential 3-layer convolutional neural network:

The size of the input array used in this model is (3662,224,224,3). Every convolutional layer has a 3x3 kernel size and 32 units are for the first layer and then there are 64 units employed in the CNN for the next two layers. Max Pooling is done at every layer, for every layer RELU activation is applied at the end there is a dense layer where the output is computed, SOFTMAX activation function has been used. The model is compiled using the 'Categorical_Crossentropy' function for computing the loss, Adam optimizer is used and accuracy metrics are used.

Model 3: Pretrained VGG 16 Model:

This is a different kind of model from the previous two, it uses a pre-trained model on another dataset. This is known as transfer learning where one model which is trained for one assignment is again used and trained for the second for example in our case, this model is pretrained for the other dataset and now it will be used for our task which is to classify the retina images into the severity of DR. The model is freezed (it is not updated by our training image data) and a sequential model is made by adding dense and dropout layers

III. RESULTS:

The following images the training accuracy of all the models which allows us to decide which one is optimal.

MODEL 1:

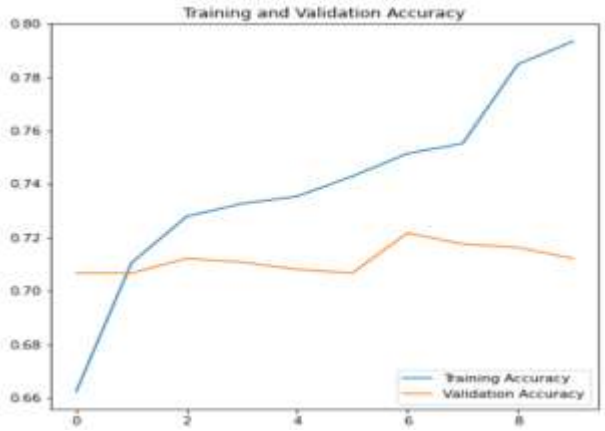


Fig 5: (a) Training and Validation Accuracy

Fig 5: (b) Training and Validation Loss

MODEL 2:

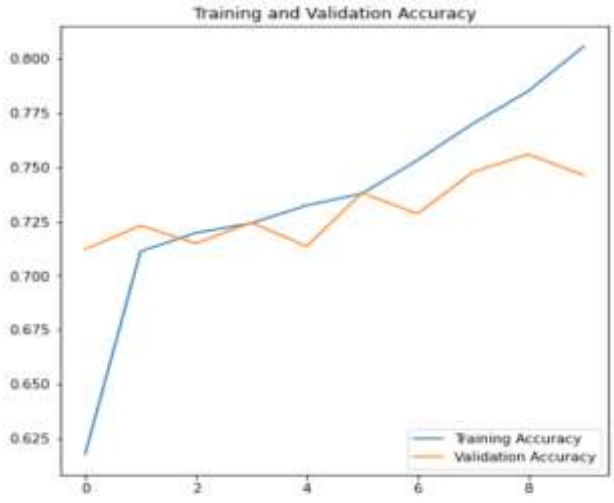


Fig 6: (a) Training and Validation Accuracy

Fig 6: (b) Training and Validation Loss

MODEL 3:

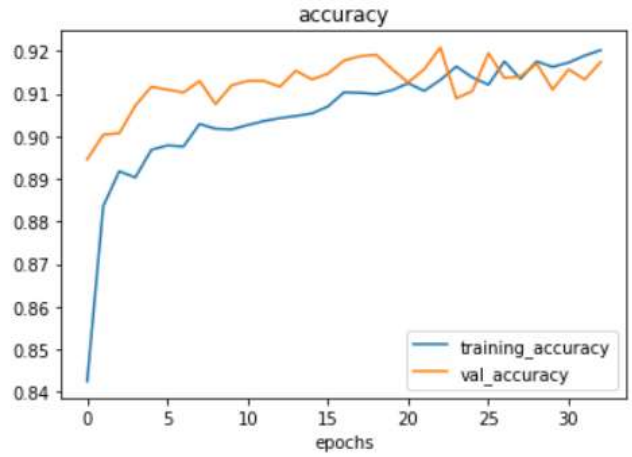


Fig 7(a): Training and Validation Accuracy

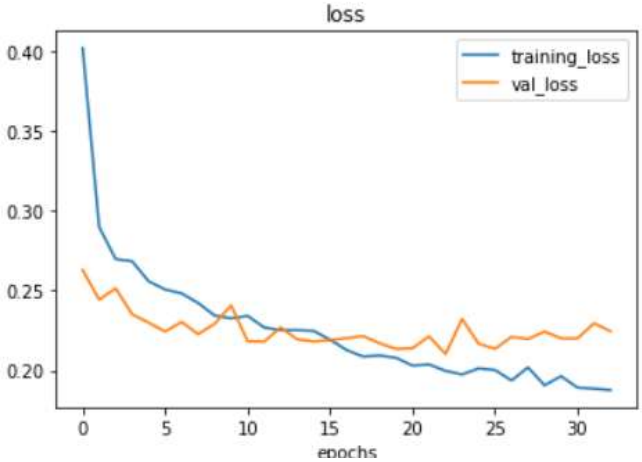


Fig 7(b): Training and Validation Loss

	MODEL 1	MODEL 2	MODEL 3
TRAINING ACCURACY	80.5%	80.07%	91.4%
TESTING ACCURACY	71.9%	74.62%	91.72%
LEARNING RATE	0.001	0.001	0.001
COMPUTATIONAL TIME	50 min	60 min	126 min
ACTIVATION FUNCTION	Softmax	Softmax	ReLu
TRAINING LOSS	0.5627	0.7824	0.2252
VALIDATION LOSS	0.5291	0.8234	0.2195

Table 1: Parameter used for Training of Neural Network Model

IV. CONCLUSION

In this paper, a brief review for the methods used for detection and classification of Diabetic Retinopathy was presented. Various processes involved in building the model were explained. The main use of this project is to make the model available in the rural areas such that doctors in rural parts can use this to detect the Diabetic Retinopathy in the early stages and help prevent permanent loss of vision

Following observations were made after comparing all models:

• Out of the first two models, model 1 has slightly better training accuracy, while the losses for model 2 is lesser (0.21) this can be due to the fact that model 1 is simpler and thus it trains easily but model 2 since is using more channels and is more tightly built it prevents more features thus the losses are less.

• Validation accuracy for model 1 stays in the range of 0.7-0.72 while for model 2 it is a little higher for around 0.74 but it is also better since with each epoch, the accuracy improves for model 2 hence overall model 2 seems to be the better model for predicting the stage of diabetic retinopathy of the patient.

• Comparing the results of model 3 with model 2 (the better of the previous 2 models) one can see that both the train set and validation set accuracy are very high for model 3 and with every epoch it also increases.

• Moreover, the training and validation loss is much lower for model 3 and it uniformly decreases with time unlike for the first two models.

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