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Deep Learning Model to Predict the Risk of Developing Diabetic Retinopathy

P. Prathyusha[1] A. Mallareddy[2] and S.V. Suryanarayana[3]
[1]PG Scholar, CVR College of Engineering/IT Department, Hyderabad, India
Email: prathyu54parakala@gmail.com
[2]Assoc. Professor, CVR College of Engineering/IT Department, Hyderabad, India
Email: dramallareddy@gmail.com
[3] Professor, CVR College of Engineering/IT Department, Hyderabad, India
Email: suryahcu@gmail.com

Abstract: **Diabetic retinopathy (DR) is a frequent eye disease that causes diabetic patients to go blind due to the damage of retinal blood vessels. Initially it is asymptotic, but it affects both the eyes and eventually causes partial or complete vision loss if it becomes severe. The most effective strategy to manage the condition is to have regular fundus photography screenings and timely management. The increased number of diabetic patients and their extensive screening needs have sparked interest in a computer-assisted, totally automatic diagnosis of DR. The early detection of DR can save the diabetic people from permanent blindness. The goal is to design a deep-learning system, specifically an Inception-v3 model, that could predict the probability of diabetic retinopathy developing within two years in patients with diabetes. The present work is developed and tested on two versions of a deep-learning system to predict the progression of diabetic retinopathy in diabetic patients who have undergone tele-retinal diabetic retinopathy screening in a primary care environment. A risk categorization technique like this could help to improve screening intervals while lowering costs and increasing vision-related outcomes.**

Keywords: **Diabetic Retinopathy, Inception-v3, deep learning, Gabor filter, fundus images.**

I. Introduction

The most prevalent cause of blindness in diabetic people is diabetic retinopathy (DR) [1]. According to the World Health Organization (WHO), there were 422 million people with diabetes in 2014, with 35 percent of them developing retinopathy because of damage to the retina's tiny blood vessels [2]. The prevalence of DR is substantially higher in some patient categories. Personalizing screening frequencies based on the possibility of diabetic retinopathy development or progression could improve the efficiency of diabetic retinopathy screening programs. We have developed a deep-learning system that can predict the risk of diabetic retinopathy using colour fundus pictures. Here, mainly our focus is on developing a deep learning machine in order to forecast the upcoming disease in the subsequent years.

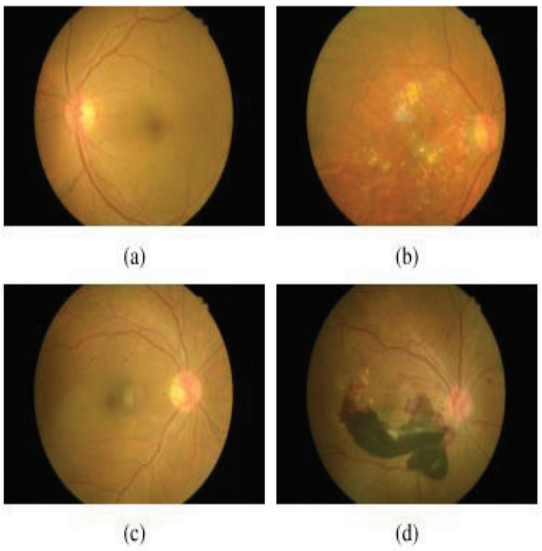

Figure 1. Sample fundus images

Fundus images which can be obtained by capturing the eyes directly are frequently used in clinical practice to diagnose DR. Exudates, micro aneurysms, and hemorrhages are some of the most prevalent lesions that indicate DR. Fundus imaging can be used to identify all these lesions [3]. A variety of fundus pictures with distinct types of lesions are shown in figure 1. Fluorescein angiography [4] can be utilized to provide a more accurate diagnosis because it can highlight small vascular structures in the retina. Fluorescein dyes, on the other hand, can provoke an allergic reaction and require working kidneys to expel, thus they are rarely available in small facilities. Currently fundus pictures are the most extensively used method for routine DR screening, due to the ease with which they may give more information and clarity of various lesions. Sample retinal images without diabetic retinopathy and with retinopathy are shown in figure 2(a) and 2(b).

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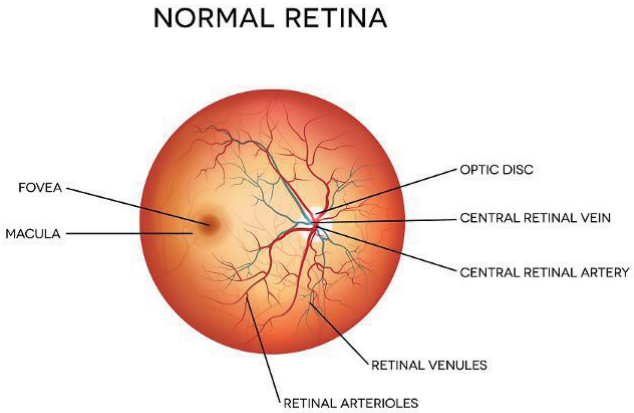

Figure 2(a). Normal Retina without Retinopathy

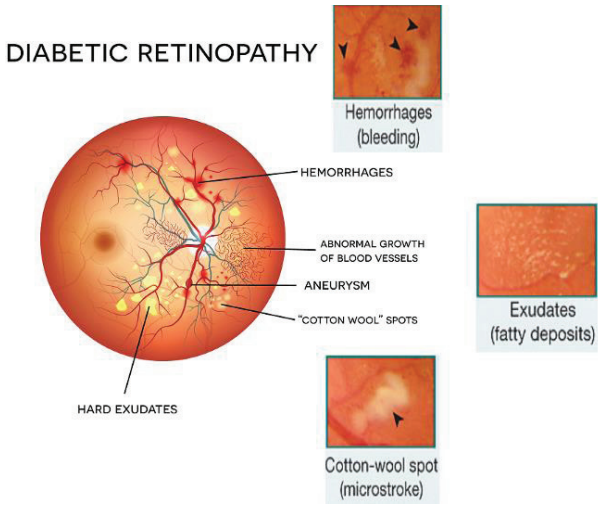

Figure 2(b). Retina with Diabetic Retinopathy

We need to change our lifestyle as it has no correct medication to prevent it. The eye vision images of a person without diabetic retinopathy and with retinopathy are shown in Figure 3(a) and 3(b).

Figure 3(a). Eye vision without retinopathy

Figure 3(b). Eye vision with retinopathy

II. Literatue Review

Deep Learning (DL) is a new advent of Machine Learning (ML) and inherits the appropriate and advantageous attributes of ML such as performing complex tasks, smart and automated, better generalization, domain knowledge, decision making etc. and efficiently applies them upon image data, thereby outperforming shallow ML algorithms. DL models have the capability to learn and to generate new features from extracted and existing features such as points, lines, edges, gradients, vessel structure, corners, boundaries etc. using representation learning.

Colin D. Jones et al. [5] stated in 2012 that they were able to estimate the incidence of diabetic retinopathy in relation to retinopathy grade at first examination and other prognostic factors. Between 1990 and 2006, a dynamic cohort study of 20,686 adults with type 2 diabetes had annual retinal photography up to 14 times. Life tables were used to estimate cumulative and annual incidence rates, and Cox regression analysis was used to identify risk factors for progression.

Convolutional networks [6] are at the heart of most cutting-edge computer vision solutions for a wide range of jobs in 2016. Since 2014, very deep convolutional networks [7] have become popular, resulting in significant improvements in a variety of benchmarks. They are looking into ways to scale up networks that use appropriately factorized convolutions and aggressive regularization to make the extra processing as efficient as possible. They demonstrate significant increases above the state of the art by benchmarking their algorithms against the ILSVRC 2012 classification challenge [8] validation set: For single frame evaluation utilizing a network with a computational cost of 5 billion multiply- adds per inference and less than 25 million parameters, the top-1 error was 21.2 percent and the top-5 error was 5.6 percent.

Gargeya et al. [8] have proposed a data-driven DL algorithm for deep feature extraction and image classification, using Deep Residual Learning (DRL) to develop a CNN for automated DR detection. The model is trained using 75,137 fundus images from EyePACS dataset

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and tested using an augmented MESSIDOR-2 dataset and E-Ophtha dataset, containing 1748 and 463 images, respectively. The proposed model has performed preprocessing, dataset augmentation, batch normalization, ReLU activation, and categorical cross entropy loss function for class discrimination using gradient boosting classifiers. The model has extracted 1024 deep features using the convolutional method. The model has detected retinal HEs, hard EXs and NV, through visualization of heatmaps. The proposed model has achieved an AUC of 0.97 with an average sensitivity of 94% and specificity of 98% on EyePACS dataset, whereas it has achieved and AUC of 0.94, with an average sensitivity of 93% and specificity of 87% on MESSIDOR-2 dataset, and an AUC of 0.95 with an average sensitivity of 90% and specificity of 94% on E-Ophtha dataset.

Eftekhari et al. [9] have proposed a Deep Learning Neural Network (DLNN), which is a two-stage training architecture consisting of two completely different structures of CNN namely a basic CNN and a final CNN, for detection of MAs, for the diagnosis of DR. The proposed model has used images acquired from datasets such as Retinopathy Online Challenge (ROC) containing 100 images and E-Ophtha-MA containing 381 images, to train and test the model. This model performs pre-processing and generates a probability map in the basic CNN to detect MAs and non-MAs, which led to a balanced dataset. This model has performed backpropagation for optimization of parameters, post processing upon the output of final CNN, and has used Stochastic Gradient Descent (SGD), Multimedia Tools and Applications dropout and binary cross-entropy loss function for training. The proposed method is assessed on ROC and E-Ophtha-MA datasets, and has achieved a sensitivity of 0.8.

Al-Bander et al. [10] have proposed a multi-sequential DL technique for detecting the centers of OD and fovea, for the detection of DR, using CNNs. The model has used the MESSIDOR database of 1200 images and 10,000 images from the Kaggle dataset, for training and testing respectively. The proposed model has enhanced the contrast of the resized image using CLAHE and has obtained the ROIs using the first CNN and performed classification using the second CNN. The proposed model is trained on augmented data using Stochastic Gradient Descent (SGD).

Mansour et al. [11] have proposed Alex Net-based DR model, which performs a comparative study on DL based feature extraction techniques against ML based feature extraction methods, and classifies the fundus images for the recognition of DR. The proposed methodology has applied a multi-level optimization measure that incorporates data collection from Kaggle dataset, preprocessing, adaptive learning Gaussian Mixture Model (GMM)-based region segmentation, Connected Component Analysis (CCA) based localization and DNN feature extraction. The model has segmented hard EXs, blot intraretinal HEs and MAs.

Deep learning algorithms were utilized in 2019 to identify diabetic retinopathy (DR) with expert-level precision. The goal of this research is to validate one of these algorithms on a large-scale clinical population and compare its performance to that of human graders [12]. A total of 25,326 gradable retinal pictures of diabetic patients were examined for DR severity and referable diabetic macular edoema in Thailand's community-based, countrywide diabetic macular edoema (DME).

The RETINARISK algorithm [13,14] was deployed at a Norwegian ophthalmology clinic in 2020. On a voluntary basis, the diabetes cohort was divided into two groups: one with variable screening intervals based on their specific risk profile, and the other with traditional fixed interval diabetic eye screening. Compliance, clinical results, safety, and cost-effectiveness were assessed between 2014 and 2019, 843 diabetic patients took part in the programme.

III. METHODOLOGY

The main objective of this work is to build a stable and noise compatible system for detection of diabetic retinopathy. This work employs the deep learning methodology for detecting the diabetic retinopathy based on severity level (No DR, Mild, Moderate, Severe and Proliferative DR). Figure 4 shows the proposed methodology. We have used the Inception V3 model to detect the Diabetic Retinopathy.

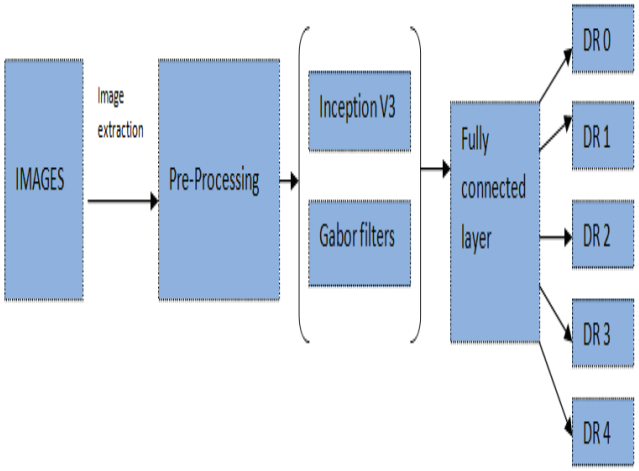

Figure 4. Proposed Methodology

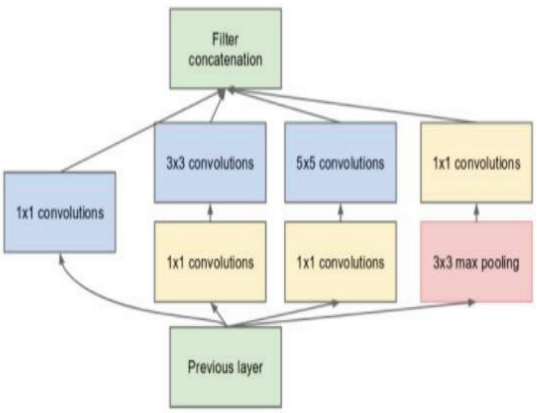

Figure 5. Inception Module with dimension reductions

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THE INCEPTION-V3 MODEL:

The initial Inception-V3 model was created for images with a resolution of 299 by 299 pixels. If the input image is blown up too much, the feature maps inside the model will be blown up as well, by reducing the depth of the model. Inception module with dimension reductions is shown in figure 5. The Inception-V3 model can be represented with two parts like feature extraction and classification. In feature extraction it performs the convolutional neural network functions and in classification it works like fully connected activation layer. As it is a pre-trained model, it can classify thousands of images. The Inception-V3 model is sophisticated, so that it gives optimized and highly effective results. The Network structure of Inception-V3 Model is shown in figure 6. The number of deeper layers in Inception-V3 are more the compared with Incetion-V1 and Inception-V3. The cost incurred to Inception-V3 is also less.

Inception-V3 architecture can be explained in a sequential manner as follows:

a) Factorized convolutions

b) Smaller convolutions

c) Asymmetric convolutions

d) Auxiliary classifier

e) Grid size reduction

Layer Index	Layer Type	Layer Configuration	Data Shape
0	Data	-	(3,299,299)
1	Convolution	(3x3,2x2,32)	(32,149,149)
2	Convolution	(3x3,1x1,32)	(32,147,147)
3	Convolution	(3x3,1x1,64)	(64,147,147)
4	Pooling	(max,3x3,2x2)	(64,73,73)
5	Convolution	(1x1,1x1,80)	(80,73,73)
6	Convolution	(3x3/1x1,192)	(192,71,71)
7	Pooling	(max,3x3,2x2)	(192,35,35)
8	Inception A	-	(256,35,35)
9	Inception A	-	(288,35,35)
10	Inception A	-	(288,35,35)
11	Inception B	-	(768,17,17)
12	Inception C	-	(768,17,17)
13	Inception C	-	(768,17,17)
14	Inception C	-	(768,17,17)
15	Inception C	-	(768,17,17)
16	Inception D	-	(1280,8,8)
17	Inception E	-	(2048,8,8)
18	Inception E	-	(2048,8,8)
19	Pooling	(avg,8x8,1x1)	(2048,1,1)
20	Softmax Output	-	4

Figure 6. Network structure of Inception-V3 Model

MODULES:

1) *Upload Diabetes Retinopathy Dataset:* Using this module we will upload dataset training images

2) *Preprocess Images:* Using this module we will read all images and then normalize images by converting all pixels values between 0 and 1. Divide each pixel values by 255 will convert image pixel between 0 and 1

3) *Train Diabetes Images Using Deep Learning:* Using this module we will train above processed images with Inception-V3 algorithm and the below code shows training image with INCEPTION

4) *Upload Test Image & Predict Disease:* After training the model we will upload new test images and then inception model will predict upcoming disease

5) *Accuracy & Loss Graph:* Using this module we will plot accuracy graph of deep learning

6) *Confusion Matrix:* It is mainly used for the classification of the classes. Confusion Matrix gives the count of correctly predicted classes and the classes which are not correctly predicted in a count format.

IV. DATASET INFORMATION

The Inception-V3 algorithm is trained on the EYEPACS [15] dataset available from the Kaggle repository. The diabetic retinopathy associated with each image has been rated on the scale of 0-4 as follows and fundus images corresponding to all stages are shown in Figure 7.

0-NoDR
1-Mild
2-Moderate
3-Severe
4 - Proliferative DR

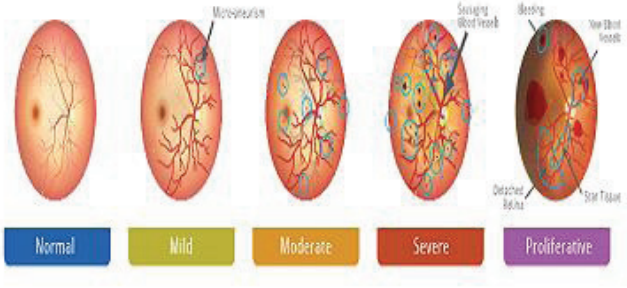

Figure 7. Fundus images at different stages of Diabetic Retinopathy

The Inception-V3 network will be used to develop a deep learning model, which may subsequently be used to new patient retinas to forecast imminent disease or the presence of the worst disease. The presence of red color cells in the photograph will indicate the presence of an upcoming disease.

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V. Experimental Results

In the initial stages of retinopathy, there will be no indications of vision related problems. As years pass, they will cause blindness to the patients. It is a symptom in both type 1 and type 2 diabetes. As the blood sugar level increases the level of complications will also increase accordingly. The fundus images that are captured on each eye (one or two images per eye) are handled as a single sample, and we have divided our data into a training set and a test set randomly. The screenshot of the main page of our project is shown in figure 8.

Figure 8. Screenshot of main page of the project

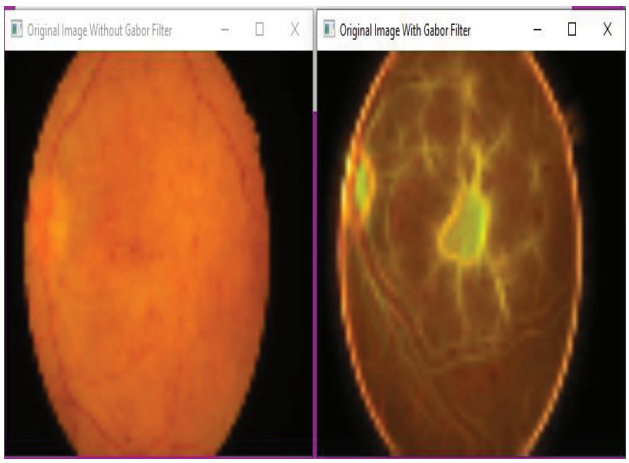

Figure 9. Preprocess images

The Gabor filter is used for finding different textures, edges, and feature extractions and it is found by using a Gaussian kernel function that is modulated by a sinusoidal wave. The filter is able to modulate over an image to extract features on different angles. The Gabor filter is a good candidate filter to be used before or during training. The preprocessed image is shown in Figure 9.

Performance evaluation consists of several standard measurements including accuracy, sensitivity, specificity, and the area under the receiver-operating characteristic curve (AUC of the ROC curve) of the automatic screening for the presence of referable DR.

TABLE I.
Comparison of Different Deep Learning Models used for DR

Deep Learning Model	Training Accuracy %	Validation Accuracy %
VGG16	77.52	75.67
Inception V3	99.29	76.82
Inception V3 with Gabor filter	99.57	82.94
Mobile Net V1	98.90	76.55
Exception	99.46	75.22

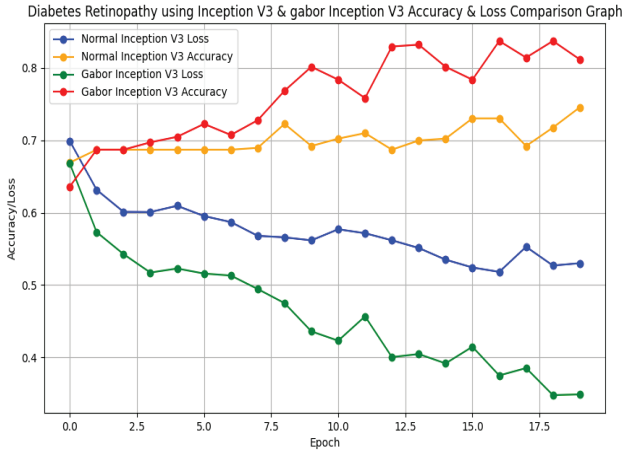

Figure 10. Accuracy & Loss comparison graph

In Table.1 we have represented the performance of different deep learning models used for the prediction of Diabetic Retinopathy. Similarly, in figure10, we have shown the comparison graph between the accuracy and loss of normal Inception v3 model and Inception v3 model with Gabor filter.

VI. Conclusions

Because of the large number of diabetes patients and the high prevalence of DR among them, there is a high demand for automatic DR diagnosis methods. Numerous accomplishments have been made thus far, with satisfying results in many subproblems such as vessel segmentation and lesion identification. In this work, the extensive experiments show that the Inception v3 model with the Gabor filter significantly improved the accuracy of the model.

However, these findings are based on limited datasets. For the real-world applications, we need to work on a high-dimensional balanced dataset. Finally, in retrospective scenarios, we have evaluated a single randomly selected eye per patient. A patient-level investigation, categorization, preferably in prospective settings, will aid in determining clinical relevance. Our findings shows that a deep-learning system could be built to improve risk stratification for developing diabetic retinopathy.

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