International Journal for Research in Engineering Application & Management (IJREAM)
ISSN : 2454-9150 Vol-07, Issue-01, APR 2021

Automatic Detection of Diabetic Retinopathy

[1]Priyank Gandhi, [2]Akshay Govardhan, [3]Swapnil Jagtap, [4]Shirish Sabnis

[1,2,3,4]Information Technology, MCT Rajiv Gandhi Institute of Technology, Mumbai, India

[1]priyankg02.pg@gmail.com, [2]swapniljagtap1999@gmail.com, [3]akshaygovardhan911@gmail.com, [4]shirish.sabnis@mctrgit.ac.in

Abstract- Diabetic Retinopathy (DR) is a disease which is a growing cause of concern for life science. Patients are struck by this disease after suffering from diabetes for a long-term and in due course, they lose their eyesight completely. The diagnosis of DR, however, remains an extended and manual process. This disease is classified differently based on the intensity of the affected capillaries in the fundus. In this project, we make an attempt towards using Convolutional Neural Network (CNN) to classify fundus retinal images as it is the most appropriate neural network used for image processing. This will help us to accurately categorize them into five classes of the disease (0-no DR, 1-mild DR, 2-moderate DR, 3severe DR, 4-proliferative DR). The CNN utilized in our work promises a powerful performance.

Keywords: Diabetic Retinopathy, Fundus, ResNet-50, supervised learning, CNN.

I. INTRODUCTION

Due to modern living style, most of the people are getting affected with Diabetes. The World Health Organization report shows that 135 million people have diabetes and therefore the number of individuals with diabetes will increase to 300 million by the year 2025. Diabetic Retinopathy (DR) may be a commonest Diabetic disease, which affects the eyes. This creates lesions such as microaneurysms, exudates, and hemorrhages. During the initial stage, most people don't notice any change in their vision. This stage is named Non-Proliferative Diabetic Retinopathy (NPDR). As the disease progresses, Non-Proliferative Diabetic Retinopathy enters the advanced proliferative stage i.e. called Proliferative Diabetic Retinopathy (PDR). It should be monitored with regular check-ups otherwise it results in blindness.

The disease is clinically classified into five stages based on the weighting of numerous features and determining the location of them - Stage0: No DR, Stage1: Mild DR, Stage2: Moderate DR, Stage3: Severe DR, and Stage4: Proliferative DR. The diagnosis comprises of detecting the presence of features responsible for the disease and further classifying the patient to its correct stage of severity, which while doing manually usually takes more time than desired. Recent advancements in computers that have developed to perform quick classifications once trained, it has opened ways to help clinicians in real-time. Automatic screening of Diabetic Retinopathy is regarded as a solution to the existing traditional diagnosis, and a few such works using image classification, pattern recognition, and machine learning, in this field, have made good progress.

We propose a method of classifying fundus images into their stages of DR by using Deep Convolutional Neural Networks.

We train our model with supervised learning on input images that gives the output indicating to which of the five stages of DR is the retina affected.

In this paper, several image processing techniques used for the detection of Diabetic Retinopathy (DR) will be discussed. Different Lesion detection techniques used for DR also are presented with appropriate results. Image processing methods are evaluated based on these results.

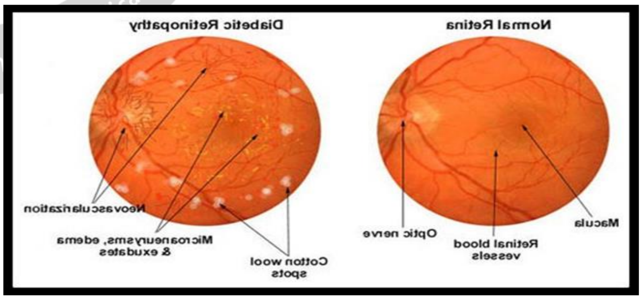

Fig 1: Normal and DR affected eye comparison

II. BACKGROUND

2.1 Current Challenges, Trends, and Issues

Diabetic retinopathy (DR) is one among the main causes of blindness within the world. It occurs when diabetes affects the circulatory blood system of the eye retina and damages the blood vessels in the retina which leads to partial or complete blindness. The effect of blood leakage from these vessels creates certain lesions in the eye retina, e.g., Microaneurysms, Hemorrhages, Neovascularization, Hard exudates, Soft exudates, Cotton wool spots, and

 DOI : 10.35291/2454-9150.2021.0133

venous loops. Non-proliferative DR (NPDR) and Proliferative DR (PDR) are two sorts of DR. Stages of DR can be classified as Mild NPDR, Moderate NPDR, Severe NPDR, and PDR.

Bayesian detection algorithm is used to classify the changes in retinal fundus images to diagnose diabetic retinopathy. This method can detect brightness variation, fundus image artifacts, outliers, and segmentation errors. Segmentation of optical disk, blood vessels, and fovea is performed to detect variations in the fundus image. The algorithm can successfully detect lesions, e.g., Microancurysm, Exudates, and cotton spots. The algorithm is did not analyze vascular changes within the fundus image.

A new hybrid vessel segmentation algorithm having morphological edge detector with TopHat segmentation technique is used to diagnose Diabetic Retinopathy. The algorithm is tested on a DRIVE image database having 20 color images. Their algorithm achieves True Positive Fraction (TPF) of 0.8214 and False Positive Fraction 1. of 0.0941. The algorithm can't detect small image region vessels and Neovascularisation.

Usman Akramused Two dimensional Gabor

Wavelet with multilayered thresholding technique proposed a methodology for vessel segmentation to detect neovascularization, a sign of Proliferative diabetic retinopathy (PDR). Gabor Wavelet is firstly used for Vessel enhancement, after multilayered thresholding, is used to create a binary mask for vessel segmentation. DRIVE and STARE databases are used to evaluate the proposed technique. Average accuracy of 95% and Std deviation of 0.03 is found.

Parisut Jitpakdee [4 presents a survey on Hemorrhage detection to diagnose diabetic retinopathy from retinal

1.) Their work reviews the latest work on common methods used for the detection of hemorrhages, e.g., Morphological processing, Neural Network, Classification, Region Growing, and Inverse method. Comparison of available methods is conducted on three bases, i.e., Image-based, Lesion-based, and Pixel-based. It is observed Image-based and Lesion-based have high sensitivity but low specificity.

Extreme Learning Machine (ELM) approach is used to propose a new methodology for blood vessel detection in retinal images. The output of pixel classification is given to ELM. It calculates grey level and fixed moment features to represent pixels. DRIVE and STARE databases are used to evaluate the results of the proposed method. Accuracy of 90% is achieved.

Feature Extraction method is also used to diagnose Diabetic Retinopathy. The adaptive histogram approach is used to extract features. Binary thresholding follows by the morphological operation is used to remove small and irrelevant objects from the image. After it, boundary tracing technique is used to detect the optical disk (OD) DRIVE and DIARETDB1 databases are used to evaluate the results based on the area, and centroid of OD.

2.2 Literature Survey

Harry, Pratt, Frans Coenen, Deborah M Broadbent, Simon P Harding, and Yalin Zheng,[2] proposed a CNN approach for diagnosis of DR from digital fundus images and perfectly organizing its severity. Developed a network with CNN architecture and data reinforcement strategy, which can identify the complicated features, involved in the classification task for example microaneurysms, exudate, and hemorrhages on the retina, and subsequently provide a diagnosis automatically and without user input. They used NVIDIA high-end graphics processor unit (GPU) on the widely available Kaggle dataset and validate inspiring results, particularly for a high-level classification task. But a little more emphasis on the initial stages of DR-enabled images is necessary.

Gardner, Keating, Williamson, Elliott, [3] at Tennent Institute of Ophthalmology, Glasgow, used Neural Networks and pixel intensity values to achieve sensitivity and specificity results of 88.4% and 83.5% respectively for yes DR and no DR. A small dataset of around 200 images splitting each image into patches was used. Firstly, with the help of a clinician, they classified the patches for features, followed by SVM implementation

Tiken Moirangthem Singh, Parismita Bharali, Chandrika Bhuyan, "Automated Detection of Diabetic Retinopathy" [4] used convolutional neural networks in exudates localization and eye fundus images for automatic categorization, which resulted in better detention of optical features that distinguish exudates.

At Indian Institute of Technology, Kanpur, Mohit Singh Solanki, [6] in his attempt to find an automated way to detect this disease in its early phase, used supervised learning methods to classify a given set of retinal images into 5 classes of retinopathy. Various image processing techniques and filters were used to enhance important features. The neural networks built for classification gave 55% accuracy on 500 data.

Alex Tamkin, Iain Usiri, Chala Fufu [7] at Stanford University also performed classification of retinal images using convolutional neural networks. Their model was trained with transfer learning for binary classification of the images. They extracted the best results using the Inception V3 model used together with ImageNet pre-trained weights in addition to dense layers on top of the model.

Cecilia S. Lee, Doug M. Baughman BS, Aaron Y. Lee, says a deep learning technique achieves high accuracy and

 DOI : 10.35291/2454-9150.2021.0133

is effective as a replacement image classification technique. Their findings showed important allegations in utilizing OCT for automated screening and therefore the development of computer aided diagnosis tools within the future [8].

Ruchir Srivastava, Lixin Duan, Damon W.K. Wong, Jiang Liu, and Tien Yin Wong, proposed the frangi filter method to deal with two complications in detecting red lesions from retinal fundus images [11]. They are false detections on blood vessels and distinctive-sized red lesions. Resulting in the detection of microaneurysms and hemorrhages efficaciously while these lesions were neighboring to blood vessels. But for different grid dimensions entertained an obstacle of high computations, needed for higher grid size.

Fulong Ren, Peng Cao, Wei Li, Dazhe Zhao, and Osmar Zaiane, proposed an ensemble-based adaptive over-sampling algorithm for overcoming the class imbalance problem in the false-positive diminution, together with boosting, bagging, random subspace as a collaborative framework and resulted in good classification performance and generalization proficiency [9].

Mahsa Partovi, Seyed Hossein Rasta, and Alireza Javadzadeh utilized the morphological function, which was applied on intensity constituents of hue saturation intensity space. To discover the exudates regions, thresholding was accomplished on all images and therefore the region of the exudate was segmented [2]. To optimize the detection efficiency, the binary morphological functions were consumed and the results were satisfying.

Thus, the investigative research on the available literature on detection and classification of Diabetic Retinopathy reveals a wide scope of deep convolutional neural networks to outperform any traditional method of the same.

III. PROPOSED SYSTEM

Deep Convolutional Neural Networks are used in our study for the classification of the fundus images based on the presence or absence of Diabetic Retinopathy. The complete work is carried out in mainly two stages, the first and foremost being the classification of fundus images into the two types of a retina having DR and not having DR. The second and the final stage is building a model that successfully classifies those images further into five c lasses namely- no DR, mild DR, Moderate DR, Severe DR, and Proliferative DR.

We incorporated Convolutional Neural Networks in our research project due to the increasing popularity of its success rate in this field. A convolutional neural network (CNN) may be a neural network that has one or more convolutional layers and is employed mainly for image processing, classification, segmentation. CNNs are basically comprised of neurons that self-optimize through learning like the conventional ANNs. The major difference between simple ANNs and deep CNNs is that the latter is used extensively in the field of pattern recognition and image classification. CNN emulates features of the visual cortex. For an image classification task specifically, a human develops the skill of recognizing the features of what he/she sees and specify them in a class of objects. CNN uses the same technique but under different regulations as unlike humans, the computer sees the numerical representation of an image.

A. <u>Dataset, Hardware, and Software:</u>

1) Dataset:

For the Five class classification problem, we used the Kaggle dataset in particular which is available for free and is open-source. Then, for convenience, we divided the entire dataset into train and test directories. For the five-class classification, the Train directory consisted of five directories No-DR, Mild-DR, Moderate-DR, Severe-DR, and Proliferative-DR. And after training of the model is done, the model is tested on the test data.

2) Hardware:

The CNN models are trained on a high-end GPU, the NVIDIA 1050 mx which contains 384 CUDA cores with the NVIDIA CUDA Deep Neural Network library (cuDNN) for GPU learning.

3) Software:

The deep learning package Keras is used to build up our CNN models, on top of the Tensorflow machine learning framework. Python libraries NumPy and matplotlib are used for preprocessing and graph plotting respectively.

B) <u>Importing necessary datasets and libraries:</u>

We have uploaded the diabetic retinopathy dataset from the Kaggle platform. We have imported the necessary libraries for exploratory data analysis. The libraries are NumPy, pandas, matplotlib, etc.

C. <u>Exploratory data analysis:</u>

Exploratory Data Analysis refers to the critical process of performing initial investigations on data to get patterns, spot anomalies, test hypotheses, and check assumptions with the assistance of summary statistics and graphical representations.

D. <u>Data Preprocessing:</u>

Preprocessing data may be a common initiative within the deep learning workflow to organize data during a format that the network can accept. For example, you'll resize image input to match the dimensions of a picture input layer. You can also preprocess data to reinforce desired features or reduce artifacts which will bias the network.

E) <u>Training:</u>

We built supervised learning models precise enough to perform the classification of input images, i.e., the CNN

 DOI : 10.35291/2454-9150.2021.0133

International Journal for Research in Engineering Application & Management (IJREAM)
ISSN : 2454-9150 Vol-07, Issue-01, APR 2021

models are trained with labeled datasets to learn the attributes and classify the retinal fundus images accordingly. There are various configurations of state-of-the-art pretrained and tested neural network architectures available such as the AlexNet, GoogleNet, VGG16, ResNet-50. All these architectures have shown excellence in different image recognition and classification tasks. We can use customized models also.

Note: The model can be changed according to the need of increasing the accuracy.

In our project, we have used the Resnet-50 model, a ResNet is a type of convolutional neural network that solves degradation problem by shortcuts or skipping connections, by short circuiting shallow layers to deep layers. We can stack Residual blocks more and more, without degradation in performance.

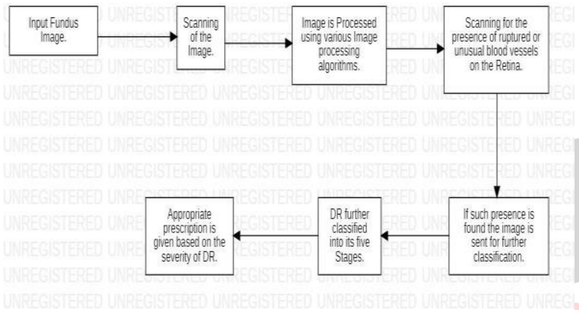

Fig 2: BLOCK DIAGRAM

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Fig 3: ResNet-50 Architecture

IV. RESULTS

1) Data

Like any real-world data set, there is noise in both the images and labels. Images may contain artifacts, be out of focus, underexposed, or overexposed. The images were gathered from multiple clinics using a variety of cameras over an extended period, which will introduce further variation.

The images are divided into 5 categories namely:

0 - No DR

1 - Mild

2 - Moderate

3 - Severe

4 - Proliferative DR

There is a total of 3662 train images, 1928 test images, train, and test CSV files.

Each model was built and evaluated using Keras on top of the TensorFlow GPU backend. Training these CNN models for fundus image classification using supervised learning, we obtained the accuracy and loss count for both training and validation data.

The model accuracy is the fraction of the right predictions that a model makes. It is usually measured in percentage of all the possible predictions using the numerical formula that states [16]:

Accuracy = Number of correct predictions/Total number of predictions

The model loss, however, unlike accuracy, is not calculated as a percentage. It is interpreted as how well the model performs for the training and validation sets of data. It is therefore calculated as the summation of the errors made by the model for each data sample in training and validation sets.

We plotted both the accuracy and loss as model loss and model accuracy graphs. This performed the models following every epoch. The results of all the trained models show a promising sign of dealing with the issues related to detecting Diabetic Retinopathy.

Using confusion matrix

Confusion Matrix:

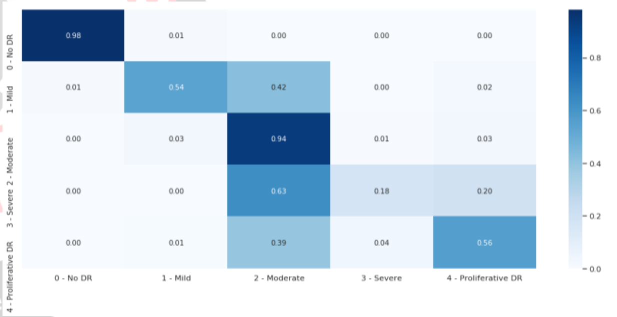

Fig 4: Confusion Matrix of the Train Data

The above displayed confusion matrix delineates the distribution of the images of fundus in the training dataset into the 5 classes of DR. The highest number of images falling into the category of Severe DR class.

Accuracy and loss graphs

1) Accuracy

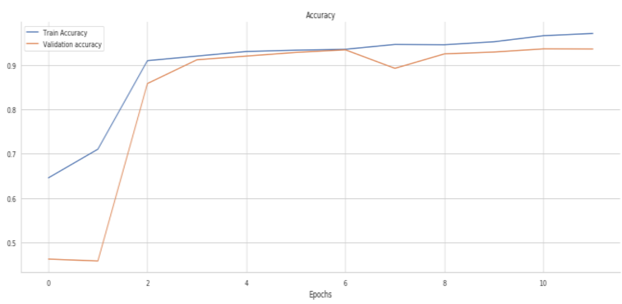

Fig 5: Accuracy Graph of the Trained Model

DOI : 10.35291/2454-9150.2021.0133

ISSN : 2454-9150 Vol-07, Issue-01, APR 2021

The above displayed Line Graph shows the accuracy attained by the model after being trained. The train accuracy is around 96% after the model is trained for 11 epochs.

2) Loss

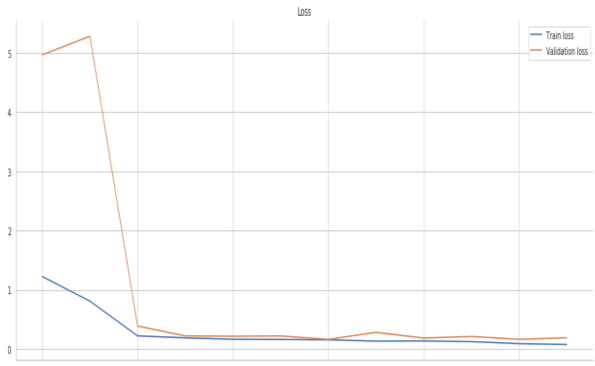

Fig 6: Loss Graph of the Trained Model

The above displayed Line Graph shows the loss in the model after being trained for 11 epochs. It can be clearly seen that the train loss suffered is constant at around 3% after 4 epochs.

V. CONCLUSION

This research work is an approach to utilizing the deep learning techniques in medical science in the diagnosis of a disease based on retinal images. We came up with the automated detection and multiclass classification of Diabetic Retinopathy into its degree of severity. We used Deep Convolutional Neural Networks in our approach. We built our neural network models to classify retinal fundus images collected from online repositories. Different models have been trained for both binary classification (No DR and Yes DR) and five class classifications (No DR, mild DR, moderate DR, severe DR, proliferative DR). It gave clarity about the Five-class classification problem of DR along with the two-class classification.

An analysis of the entire work is successful in stating the significance of the difference in model architectures. Adding deeper layers and adjusting hyperparameters across the network builds separate models with a difference in results. This paved the way to further research on deep neural network architectures. The basic limitations of our work were the inconsistent dataset and the hardware specifications. A system with higher GPU specifications is expected to build more precise CNN models if trained with a larger and cleaner dataset. This leaves us with the scope to develop and train better CNN models to further improve results. Finally, the probability of saving a patient who was about to acquire blindness due to diabetes decreases significantly, thus, making a difference.

REFERENCES

[1] Pratt, Harry & Conan, F.B.D. P.H.S. Z.Y.: Convolutional neural networks for diabetic retinopathy. Procedia Computer Science (2016).

[2] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5961805/ Automatic detection of diabetic retinopathy using deep learning.

[3] Gardner, G., K.D.W.T.E.A.: Automatic detection of diabetic retinopathy using an artificial neural network: a screening tool.

[4] Tiken Moirangthem Singh, Parismita Bharali, Chandrika Bhuyan, "Automated Detection of Diabetic Retinopathy" 2019 Second International Conference on Advanced Computational and Communication Paradigms (ICACCP).

[5] Shojaeipour, A., N.M.J. H.N.: Using image processing methods for diagnosis diabetic retinopathy. EEE International Symposium on Robotics and Manufacturing Automation (ROMA). doi:10.1109/roma.2014.7295879 (2014).

[6] Solanki, M.S.: Diabetic retinopathy detection using eye images (April 18, 2015).

[7] Alex Tamkin, Iain Usiri, C.F.: Deep CNNs for diabetic retinopathy detection.

[8] Cecilia S. Lee MD, Doug M. Baughman B, Aaron Y. Lee MD MSCI https://www.researchgate.net/publication/311668640_Deep_learning_is_effective_for_the_classification_of_OCT_images_of_normal_versus_Age-related_Macular_Degeneration

[9] Methods to evaluate segmentation and indexing techniques in the field of retinal ophthalmology(messidor), http://www.adcis.net/en/DownloadThirdParty/Messidor.

[10] Keras: The Python Deep Learning Library. Keras Documentation, keras.io/.

[11] Deep learning-moving beyond shallow machine learning since 2006, http://deeplearning.net/software/tensorflow/.

 DOI : 10.35291/2454-9150.2021.0133