iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 **Issue:** X **Month of publication:** October 2021

DOI: https://doi.org/10.22214/ijraset.2021.38628

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue X Oct 2021- Available at www.ijraset.com

Automated Detection and Classification of Diabetic Retinopathy using ConvNets

Aavani B[1], Anjali M S[2], Sreelakshmi S Y[3], Sreema M S[4], Lekshmi P Govind[5]
[1, 2, 3, 4]*Student,* [5]*Assist. Professor, Department of Electronics & Communication Engineering, Dr. APJ Abdul Kalam Technological University, Kerala, India*

Abstract: ***Diabetic retinopathy is the leading cause of blindness in diabetic patients. Screening of diabetic retinopathy using fundus image is the most effective way. As the time increases this DR leads to permanent loss of vision. At present, Diabetic retinopathy is still being treated by hand by an ophthalmologist which is a time-consuming process. Computer aided and fully automatic diagnosis of DR plays an important role in now a day. Data-set containing a collection of fundus images of different severity scale is used to analyze the fundus image of DR patients. Here the deep neural network model is trained by using this fundus image and five-degree classification task is performed. We were able to produce an sensitivity of 90%.***
Keywords: Confusion matrix, Deep convolutional Neural Network, Diabetic Retinopathy, Fundus image, OCT

I. INTRODUCTION

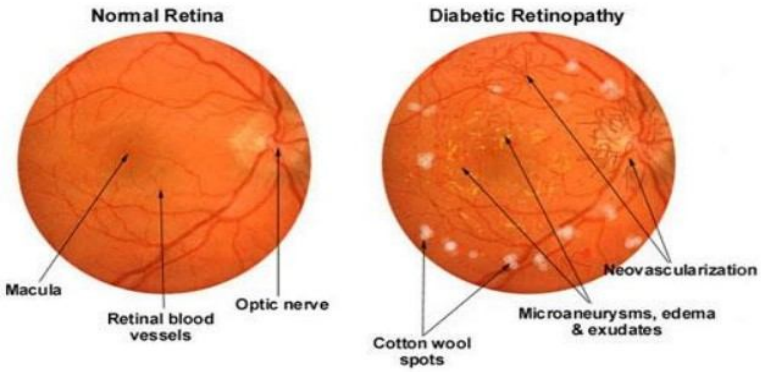


Figure 1: Normal Vs DR Retina

In our modern era eye related diseases increased, due to lack of care and treatment. Diabetic retinopathy is the most common among them, which ultimately leads to permanent vision loss of the victim. Diabetic patients with high sugar level in blood can cause damage to the blood vessels in the retina. Diabetic retinopathy is a serious sight-menacing complication of diabetics. Patients with high sugar level in blood can cause damage to the blood vessels in the retina. Which leads to leakage or swelling of blood vessels or even stopping blood flow through it. All these may affect your vision. The early stages of diabetic retinopathy ave no visual symptoms. So it is recommended that everyone with diabetes must have a comprehensive dilated eye examination once a year. Detection and treating the aliment at an earlier stage can limit the potential for significant vision loss from diabetic retinopathy. NPDR (Non-proliferate diabetic retinopathy) and PDR (Prerogative diabetic retinopathy) are the two main stages of diabetic eye diseases. Among these PDR is very serious which affect both central and peripheral vision of eye. It is the advanced stage here new vessels began to grow inside the retina which often bleed into the vitreous. It is about 75% chance of developing PDR for a patient with severe NPDR[1]. According to International Clinical Diabetic Retinopathy Disease Severity Scale. The DR severity is classified into five stages. They are NORMAL, MILD, MODERATE, SEVERE, and PROLIFERATE. The treatment also varies on the basis of the severity of DR. Diagnosis of DR is mainly performed by using fundus images obtained by fundus photography. From these fundus image the lesions that indicates DR can be identified.

In early days fundus ophthalmoscopy and fluorescein angiography are used for the diagnosis of DR. But later it was identified that these methods do not contribute much to the evaluation of DR and its thickness profile. So as a result, OCT (Optical Coherence Tomography) was introduced to overcome the limitations of the existing technologies. Optical Coherence Tomography (OCT) is an imaging modality that is used extensively for ophthalmic diagnosis, which produces high resolution and cross-sectional images of retina. The population of diabetic patients is increasing day by day. Regular screening is most important in case of DR. In our conventional method the fundus image is diagnosed by an expert ophthalmologist. But due to the rapid rise in the population of diabetic patients the ophthalmologist cannot reach each and every diabetic patient. The gap between the population of diabetic patients and expert ophthalmologist become wider as the time increases. As a result, more people get untreated. So, as a result, a computer aided and fully automatic diagnosis of DR is achieved by using deep neural network (DNN). Advancement in this field is increasing day by day which reduces the human intervention in the diagnosis process [2].

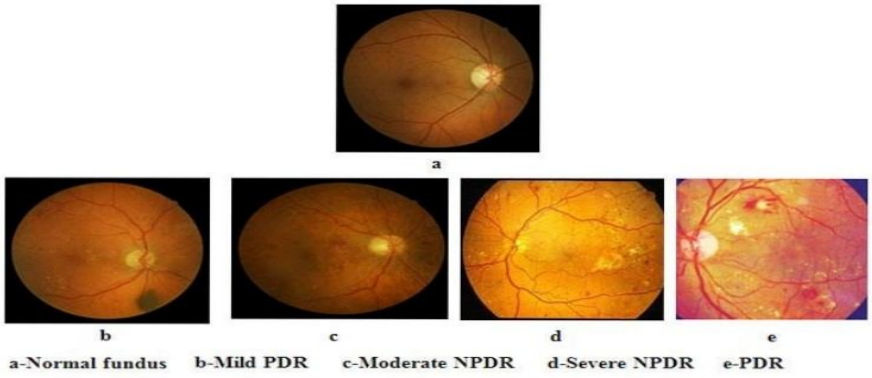


Figure 2: Different stages of DR

II. LITERATURE SURVEY

Junjun Pan (2018) proposed a method for DR detection based on deep convolutional neural networks for localization of discriminative regions[3]. They developed a novel ResNet18-based CNN architecture for DR detection, which is trained with weak supervision using image-level annotations only without object or patch-level labels. The retinal images were classified into 4 classes; No DR, Mild DR, Moderate DR, Severe DR and Proliferative DR. The dataset was first pre-processed, followed by data augmentation. Then they provided a regions scoring map (RSM) to show certain regions of the fundus image in terms of severity level. Also, this CNN architecture could achieve the comparative prediction performance with less parameters, which can be useful for large-scale datasets. This method achieved 78.4% accuracy in test data.

Sharish qummar (2019) introduced a deep learning ensemble approach for DR detection[4]. Often, trained experts examine the colorful images of the fundus to detect this deadly disease. This a physical examination of this condition (by doctors) is tedious and erroneous. So, a different computer vision-based techniques proposed to automatically detect DR and its distinct phases from the retina pictures. However, these methods cannot encrypt the complexities and can only work classify different categories of DR with very low accuracy especially, with early stages. Modify retina image databases to train one of five deep Convolution Neural Network Types (CNN) (Resnet50, Inceptionv3, Xception, Dense121, Dense169) coding for rich people features and improve the classification of the various DR categories. The results indicate that the proposed integration model, it works better than other advanced methods too able to find all categories of DR.

G N Girish, Bibhash Thakur , Sohini Roychowdhury, Abhishek R. Kothari and Jeny Rajan proposed a method Segmentation of Intra-Retinal Cysts from Optical Coherence Tomography Images using a Fully Convolutional Neural Network Model [5]. Optical Coherence Tomography (OCT) is an imaging modality that is used extensively for ophthalmic diagnosis, near-histological visualization and quantification of retinal abnormalities such as cysts, exudates, retinal layer disorganization,etc. The proposed method counteracts image noise variabilities and trains FCN models on OCT sub-images from the OPTIMA cyst segmentation challenge dataset (with four different vendor-specific images, namely, Cirrus, Nidek, Spectralis, and Topcon). Further, optimal data augmentation and model hyper-parametrization is shown to prevent over-fitting for IRC area segmentation. The proposed method is evaluated on the test data set with a recall/precision rate of 0.66/0.79 across imaging vendors. The Dice correlation coefficient of the proposed method outperforms that of the published algorithms in the OPTIMA cyst segmentation challenge with a Dice rate of 0.71 across the vendors.

Adal (2017) presented a system for automatic detection and classification of DR using the retinal changes of red lesions in fundus images [6]. The red lesions are one of the earliest sign of DR. Initially the illumination normalization & registration step is performed for the visibility of the retinal features of the given fundus image. After that, the retinal change locations are identified. Several descriptive features are extracted from each candidate region. Finally, the detected change locations are classified as a change due to DR or not based on the small red lesions using the SVM classifier which is trained using the dataset from Rotterdam Eye Hospital.

III.METHODOLOGY

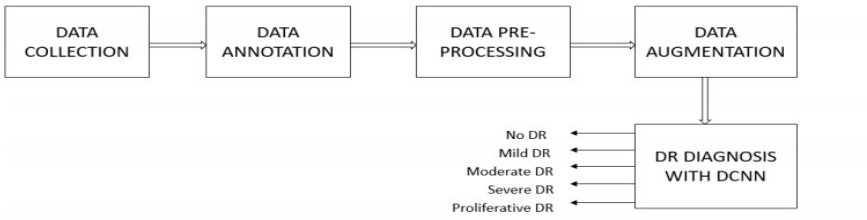


Figure 3: Block Diagram of proposed method.

Data-set construction: In the Data-set Construction section, Data collection & Data Annotation are the main construction step of data construction. Here, Re-sized 2015 & 2019 Blindness Detection Images is used as dataset. There are fundus photographs of the right &left eyes of 35126 American citizens in the dataset. In Data Annotation, the fundus images in the Data-set were labeled into five degrees[7]: No diabetic retinopathy (label 0), Mild diabetic retinopathy (label 1), Moderate diabetic retinopathy (label 2), Severe diabetic retinopathy (label 3), Proliferate diabetic retinopathy (label 4). Data preparation: Data preprocessing and Data Augmentation are main step in data preparation. Noise removing is performed in data preprocessing[8]. The augmentation is done shortages in data is mitigated and fully utilize for our purposes. In data preprocessing step consist of three steps; they are size normalization, shape normalization & color normalization. These are preformed to convert the fundus images into a uniform manner and to ensue that the machine learn the true features of the DR. In data augmentation the image flipped in horizontally & vertically, and randomly rotate the image, randomly zoom in or out in the range to extract the desired features the image[9].

DR diagnosis with Deep Convolutional Neural Network(DCNN): Neurons are the are basic computational unit in neural networks . The three basic components in the CNN are : the Convolutional layers, the in-place activation operation, and the pooling layers.here, here several connected layers & classification layers at the end performs the classification tasks. In this method, 5 layers of CNN model is build. This model is saved as json file and which is used for the grading of severity[10].

IV.SYSTEM REQUIREMENTS

A. Software Requirements

Operating system -Windows 10.

Programming Language -python 3.6.

Platform used - Kaggle.

1) Libraries used

a) NumPy: For working with arrays we used NumPy library. NumPy stands for Numerical Python. It is an open source project and we can access it freely.

b) Pandas: Data science/data analysis and machine learning tasks can be performed by using pandas python library.

c) Tensorflow: For fast numerical computing we use Tensorflow python library and which is released by Google.It is a foundation library that can be used to create Deep Learning models directly.

d) Matplotlib: For amazing visualization library in Python for 2D plots of arrays we use matplotlib. Matplotlib is build on NumPy arrays for visualizing multi-platform datas.

e) Keras: It is run on top of TensorFlow & it act as minimalist python library .

f) os: The os module in Python provides functions it provide function for interacting with the operating system. It is sub-unit of Python's standard utility modules. Depending on the functionality, the module provides a portable way of using operating system .

g) sys: sys stands for System-specific parameters and functions.

h) Open CV: it is a cross-platform library used for develop real-time computer vision applications.

B. Hardware Requirements

1) Intel Core i5 8th Gen
2) 8 GB RAM.
3) Platform used -Google Colab.
4) NVIDIA GeForce MX130 (2 GB GDDR5)

V. EXPERIMENTAL SETUP

1) *Importing Libraries:* First of all we want to import python libraries such as Numpy, Pandas, Tensorflow, Matplotlib, Keras, OS, sys, Seaborn, Scikitplot, Scikit learn, Json, Open CV and some of its sub libraries by using the importing statements.

2) *Importing Dataset:* In importing dataset , first importing aptos-2019 blindness detection data csv file[11].Then visualizing the dataset which is shown in figure 4.

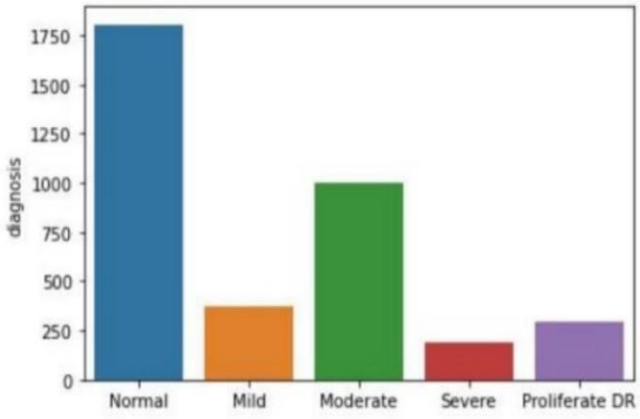


Figure 4: Visualizing dataset

Next, we want to import the diabetic retinopathy resized data from the kaggle competition 2015 csv file named dataset1 and visualizing the dataset1 as shown in figure 6. We will take 900 images in total for In each class we select about 900 images .

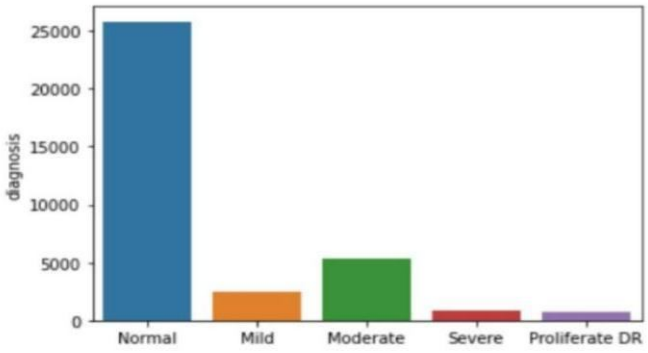


Figure 5: Visualizing dataset 1

3) *Preprocessing the Imported Data:* We got the fundus image from the patients of varying ethnicity, age groups and varied levels of lightning in the fundus photography from the dataset. Due to the variations in the brightness and other parameters of fundus image, it will affect the pixel values. Later may create unnecessary variations in the classification level. To overcome these we performed preprocessing which contains the size, shape and color normalization steps[12]. In this Size, Shape & color normalization; The first step is to resize different images into a uniform scale. And later the color normalization is performed, the different devices produce images with different color, temperatures & illumination conditions. So we want to normalize the color of the fundus image. So we used a single gray channel to reduce the complexity & processing time.

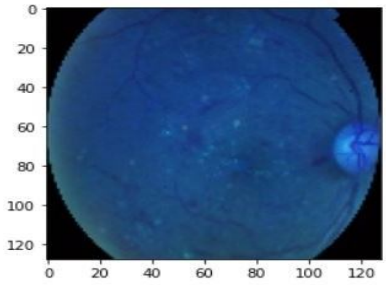


Figure 6: Image after size & Shape normalization

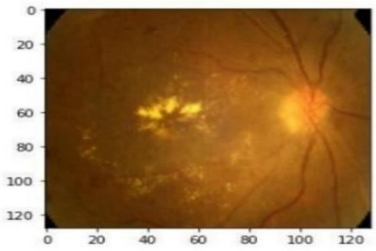


Figure 7: Image after color

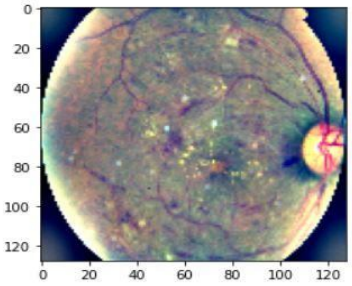


Figure 8: Image after color normalization

4) *Image Augmentation:* The image augmentation techniques are used to mitigate shortages in data and fully utilize the data that are available. Here we used the online augmentor is used.the data augmentation consist of the following steps.

a) Flip the image horizontally
b) Rotate the image
c) Zoom the image
d) Shifting image width wise
e) Shifting the image height wise

The augmentation is performed in each and every fundus images in the dataset.

5) *Visualizing Balanced Dataset & scaling/normalising Image Dataset:* In normalization we rescaled the data from the original scale to a values in the range of 0 and 1. It is performed to achieve faster convergence and speed up the learning. The goal of normalization is to change the values of numeric columns in the dataset to a common scale, without distorting differences in the ranges of values. Ideally, detection rate for each of the classes maybe same or with a slight variation.

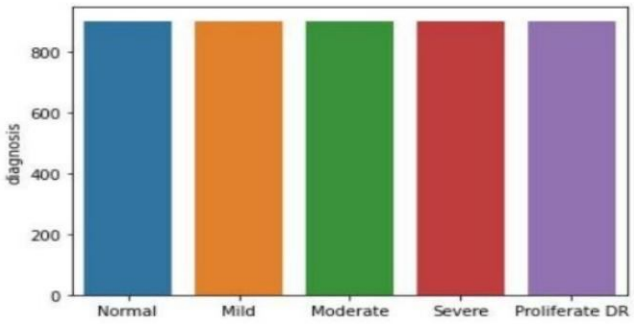


Figure 9: Visualizing balanced dataset

6) *Splitting of Dataset in Train and Test Data:* For evaluating the deep learning models, so we wants to separate the data into training and testing sets. A major part of is used as training and a small part selected for testing . It is helps to better understand the characteristics of the model . Firstly the training set is used processes the model and finally the test set is used to compare the obtained result. For splitting the data into training &testing dataset, we use train_test split() from the data science library scikit_learn. For unbiased prediction & detection of performance, the splitting of data must essential. The training of model is performed by using this training set and the unbiased evaluation of the final model is performed by using the test set.

7) *Training of Model:* We going to design a convolutional neural network model using stratified k-fold cross validation technique.

Designing the convolutional neural network model.

Here the input image is applied to a CNN. A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain. In CNN the word convolutional refers to the mathematical function of convolution. Here in convolutional operation two functions are multiplied and the result is an another function which express, how the shape of one function is modified by the another. Here also two matrices are multiplied to get an output. This output is used to extract the features from the input image [13]. Feature extraction and a fully connected layer are 2 main parts of CNN architecture. In feature extraction, a convolution tool is used to exact the features from the image for the analysis and the fully connected layer help to predict the class of the image based on the output obtained from the convolution process. The convolutional layers, pooling layers, and fully- connected (FC) layers are the three types of layers in CNN network [14]. Along with the three important layers. There are two important parameter i.e, the dropout layer and the activation functions.

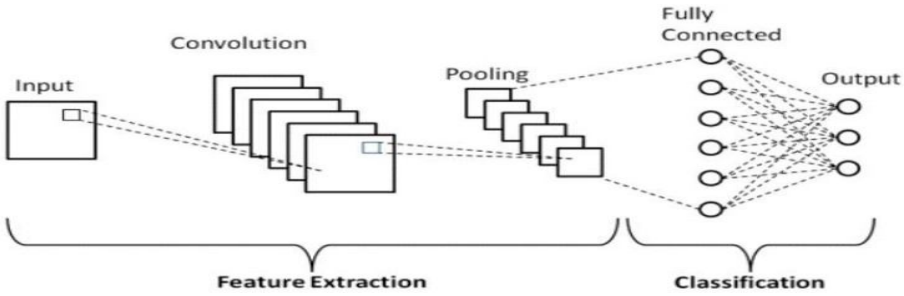


Figure 10: CNN Model

8) *Convolutional Layer:* It is the first layer of the CNN. Feature extraction is performed in this layer. Here the input image is convoled with a filter of a particular size MxM. Feature map is the output obtained from this layer and which contain information regarding the corners and edges of the image.
9) *Pooling Layer:* The output from the covolutional layer is applied to a pooling layer, the main aim of this pooling layer is to decrease the size convolved feature map. As a result we can reduce the computational costs. In most cases, a Convolutional Layer is followed by a Pooling Layer. The primary aim of this layer is to decrease the size of the convolved feature map to reduce the computational costs. In Max Pooling, the largest element is taken from feature map. Average Pooling calculates the average of the elements in a predefined sized Image section. The total sum of the elements in the predefined section is computed in Sum Pooling. The Pooling Layer usually serves as a bridge between the Convolutional Layer and the FC Layer.
10) *Fully Connected Layer:* The Fully Connected (FC) layer is used to collect the neurons between two different layers. The classification process mainly begins from this stage.the input of FC layer is a flattened image and this image undergo sum mathematical operations.
11) *Dropout:* In dropout layer, few neurons are droppedout from the neural network during the training process to reduce the size of the model as well as we eliminate the over-fitting.
12) *Activation Function:* Here a we build a new CNN model by using Keras and Tensorflow activation functions is used here are the ReLU, Softmax, tanH and the Sigmoid functions. Each of these functions have a specific usage. Pooling operation is done by using Max Pooling,

A. *Using Stratified K-Fold Cross Validation Technique To Split The Training Data Into Training And Validation Sets*

Stratified K-Folds cross-validator is used to split the data into train/test sets. The objective of cross- validation is a variation of K Fold that returns stratified folds. Here the training data is splitted into K Fold folds. The first k-1 folds are used for train the model, and the holdout kth fold is used as the test set.

B. *Compile and Train the Model for Each Split*

We want to compile & train the model for each split. The training dataset is used to prepare a model, then train it. We pretend the test dataset is new data where the output values are withheld from the algorithm. We gather predictions from the trained model on the inputs from the test dataset and compare them to the withheld output values of the test set

C. Plot the Training Curves for Each Split.

The training curves are plotted for each split which are as follows;

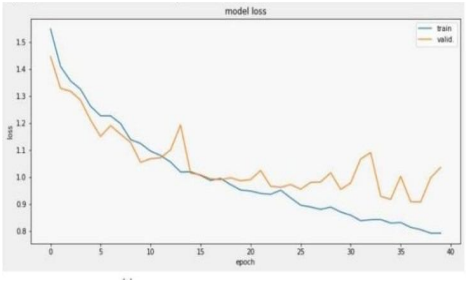


Figure 11: Training curve of loss function for iteration 1

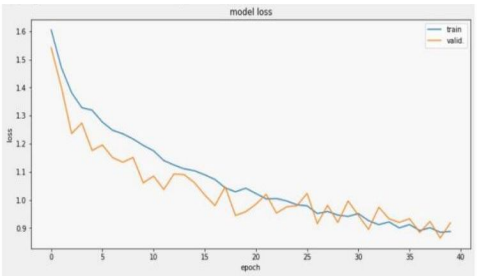


Figure 12: Training curve of loss function for iteration 2

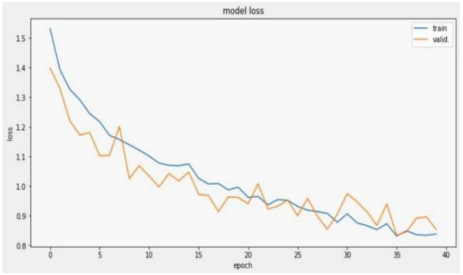


Figure 13: Training curve of loss function for iteration 3

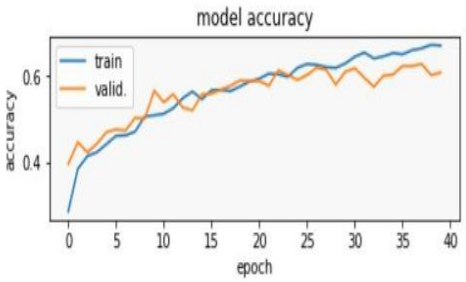


Figure 14: Training curve of accuracy for iteration 1

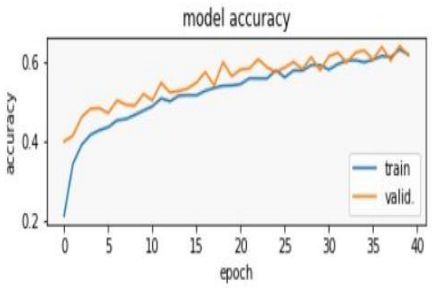


Figure 15: Training curve of accuracy for iteration 2

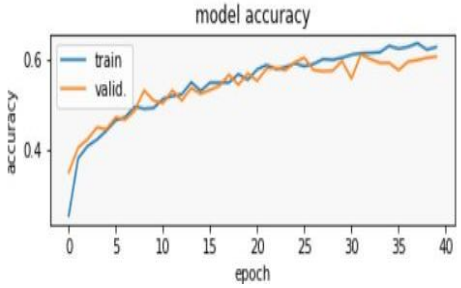


Figure 16: Training curve of accuracy function for iteration 3

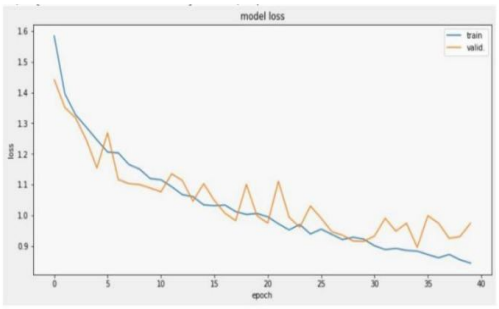


Figure 17: Training curve of loss function for iteration 4

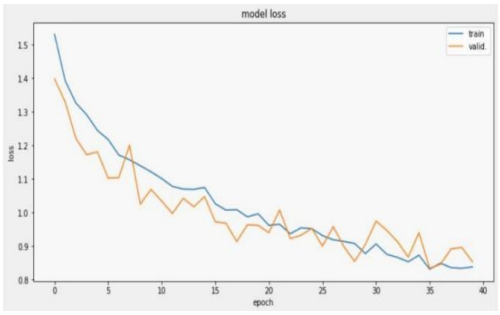


Figure 19: Training curve of loss function for iteration 5

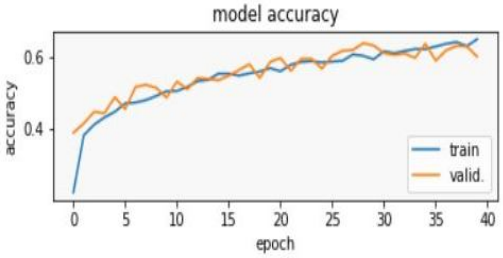


Figure 18: Training curve of accuracy for iteration 4

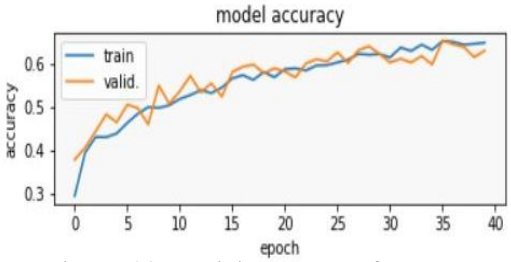


Figure 20: Training curve of accuracy for iteration 5

D. Analysis of Training Model

We are able to achieve an Accuracy about 68% for the training data prediction .the Confusion Matrix of training data prediction is shown in figure 22. Also the classification report of training set is given below

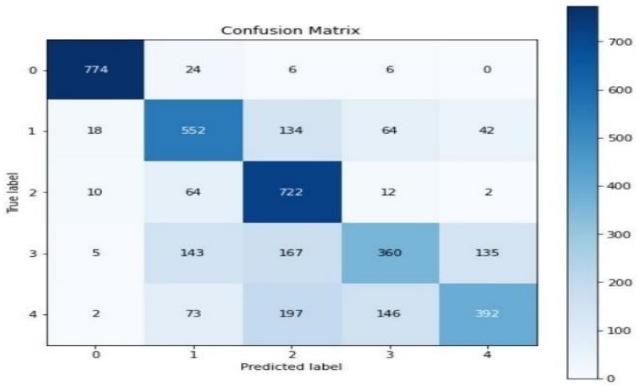


Figure 21: Confusion matrix of train data

The classification report of training set is as follows:

Classification Report of training set :

	precision	recall	f1-score	support
No DR	0.84	0.99	0.91	810
Mild	0.60	0.65	0.63	810
Moderate	0.61	0.89	0.72	810
Severe	0.65	0.40	0.50	810
Proliferate DR	0.72	0.49	0.58	810
accuracy			0.68	4050
macro avg	0.69	0.68	0.67	4050
weighted avg	0.69	0.68	0.67	4050

Figure 22: classification report of training set

E. Analysis of Test Results

Accuracy of test prediction = 0.65

Confusion Matrix of testing data prediction is shown in figure 24.

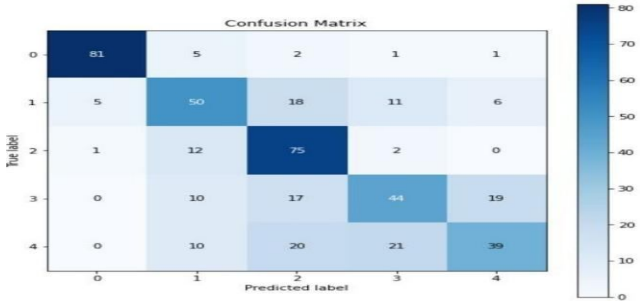


Figure 23: Confusion matrix of test data

The final classification report after train & test is as follows:

Classification Report

	precision	recall	f1-score	support
No DR	0.98	0.96	0.97	90
Mild	0.61	0.59	0.60	90
Moderate	0.67	0.79	0.72	90
Severe	0.44	0.61	0.51	90
Proliferate DR	0.69	0.34	0.46	90
accuracy			0.66	450
macro avg	0.68	0.66	0.65	450
weighted avg	0.68	0.66	0.65	450

Figure 24 : Final classification report

VI. RESULTS AND DISCUSSION

We compared our model with the existing technologies and we are able to produce a high sensitivity than other techniques[3-6].

Table 1: Comparison of different techniques of Accuracy.

Techniques	Accuracy
Automated system for the Detection & classification of Retinal changes due to red lesions in Longitudinal fundus image[3].(A)	66
A Deep Learning Ensemble approach for DR Detection[4].(B)	83.68
Segmentation of Intra-retinal cysts from optical coherence tomography images using a fully CNN Model[5].(C)	85
Diagnosis of DR using DCNN[6].(D)	68

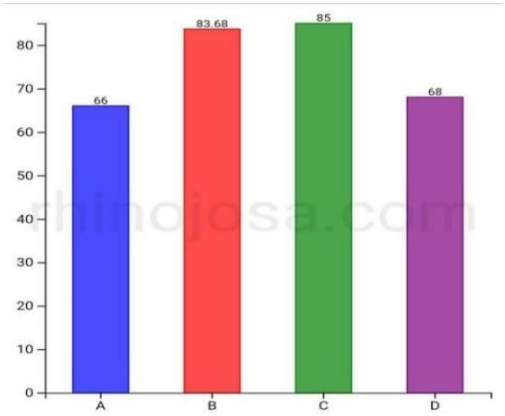


Figure 25 : Comparison of accuracy

Table 2: Comparison of different techniques of Sensitivity.

Technique	Sensitivity
Automated system for the Detection & classification of Retinal changes due to red lesions in Longitudinal fundus image[3]. (A)	80
A Deep Learning Ensemble approach for DR Detection[4].(B)	54.47
Segmentation of Intra-retinal cysts from optical coherence tomography images using a fully CNN Model[5].(C)	66
Diagnosis of DR using DCNN[6]. (D)	90

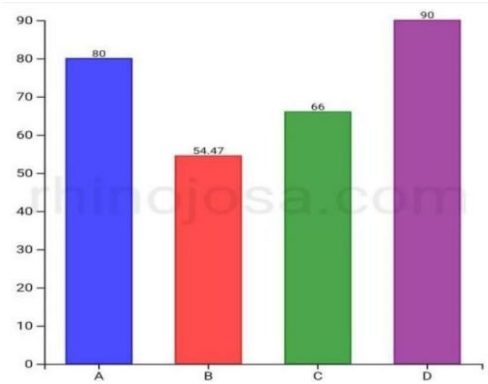


Figure 26 : Comparison of Sensitivity

VII. CONCLUSION & FUTURE SCOPE

Diabetic Retinopathy is a complication of diabetes mellitus, which progressively damages retinal blood vessels and may result in vision loss and even blindness if not diagnosed and treated adequately. Regular eye examination is necessary for timely detection and treatment of DR. The current eye care practice for screening DR involves examination of multiple field fundus images for pathognomonic abnormalities by a trained expert, but the chances of faults are also great. Using optical coherent tomography is very costly. For clinical application, systems that can give DR severity directly are more favorable and practical. However, current results for multi-class severity grading are still not good enough for clinical application. Automatic grading of DR using deep neural networks can be an important addition to the manual clinical applications. We have used our own built CNN model which is used as the model for training & testing of the Data-set. We have achieved 68% accuracy for the train data and overall of about 66% for the train & test data. We have also achieved a support of 90 and precall upto 96 and precision of 98 for several classes.

We designed only the software part. We can implement this system in hosptial along with some hardware part such as fundus image photographing device and an output device. Thus it become more advanced and easily accessible. And also we can improve our accuracy as much as we want, by changing the epoch value. Thus it become more efficient. We can use the same system for the diagnosis by making some changes in the design process and the dataset.

VIII. ACKNOWLEDGMENTS

The authors express their wholehearted thanks to their college management, faculties and parents for continuous support and mentoring. And also like to thank the editor and the reviewers for their thoughtful comments and efforts towards improving the manuscript. Any remaining errors are the sole responsibility of the authors.

REFERENCES

[1] L. Qiao, Y. Zhu and H. Zhou, "Diabetic Retinopathy Detection Using Prognosis of Microaneurysm and Early Diagnosis System for Non-Proliferative Diabetic Retinopathy Based on Deep Learning Algorithms," in IEEE Access, vol. 8, pp. 104292-104302, 2020

[2] Z. Gao, J. Li, J. Guo, Y. Chen, Z. Yi and J. Zhong, Diagnosis of Diabetic Retinopathy Using Deep Neural Networks, in IEEE Access, vol. 7, pp. 3360-3370, 2019.doi:10.1109/ACCESS.2018.2888639

[3] P. Junjun, Y. Zhifan, S. Dong and Q. Hong. Diabetic Retinopathy Detection Based on Deep Convolutional Neural Networks for Localization of Discriminative Regions, 2018 International Conference on Virtual Reality and Visualization (ICVRV), Qingdao, China, 2018, pp. 46-52.

[4] S. Qummar et ali. A Deep Learning Ensemble Approach for Diabetic Retinopathy Detection, in IEEE Access, vol. 7, pp. 150530-150539, 2019. doi: 10.1109/ACCESS.2019.2947484

[5] G. N. Girish, B. Thakur, S. R. Chowdhury, A. R. Kothari and J. Rajan, Segmentation of Intra-Retinal Cysts From Optical Coherence Tomography Images Using a Fully Convolutional Neural Network Model, in IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 1, pp. 296-304, Jan. 2019, doi: 10.1109/JBHI.2018.2810379.

[6] K. M. Adal, P. G. van Etten, J. P. Martinez, K. W. Rouwen, K. A. Vermeer and L. J. van Vliet, "An Automated System for the Detection and Classification of Retinal Changes Due to Red Lesions in Longitudinal Fundus Images," in IEEE Transactions on Biomedical Engineering, vol. 65, no. 6, pp. 1382-1390.

[7] Gayathri S., Gopi, V.P. & Palanisamy, P. Automated classification of diabetic retinopathy through reliable feature selection. Phys Eng Sci Med 43, 927–945 (2020).

[8] S. Sreng et al., "Feature extraction from retinal fundus image for early detection of diabetic retinopathy," IEEE Region 10 Humanitarian Technology Conference, Sendai, 2013, pp. 63-66, 2013.

[9] A. A. M. Al-Saffar, H. Tao and M. A. Talab, "Review of deep convolution neural network in image classification," 2017 International Conference on Radar, Antenna, Microwave, Electronics, and Telecommunications (ICRAMET), Jakarta, Indonesia, 2017, pp. 26-31.

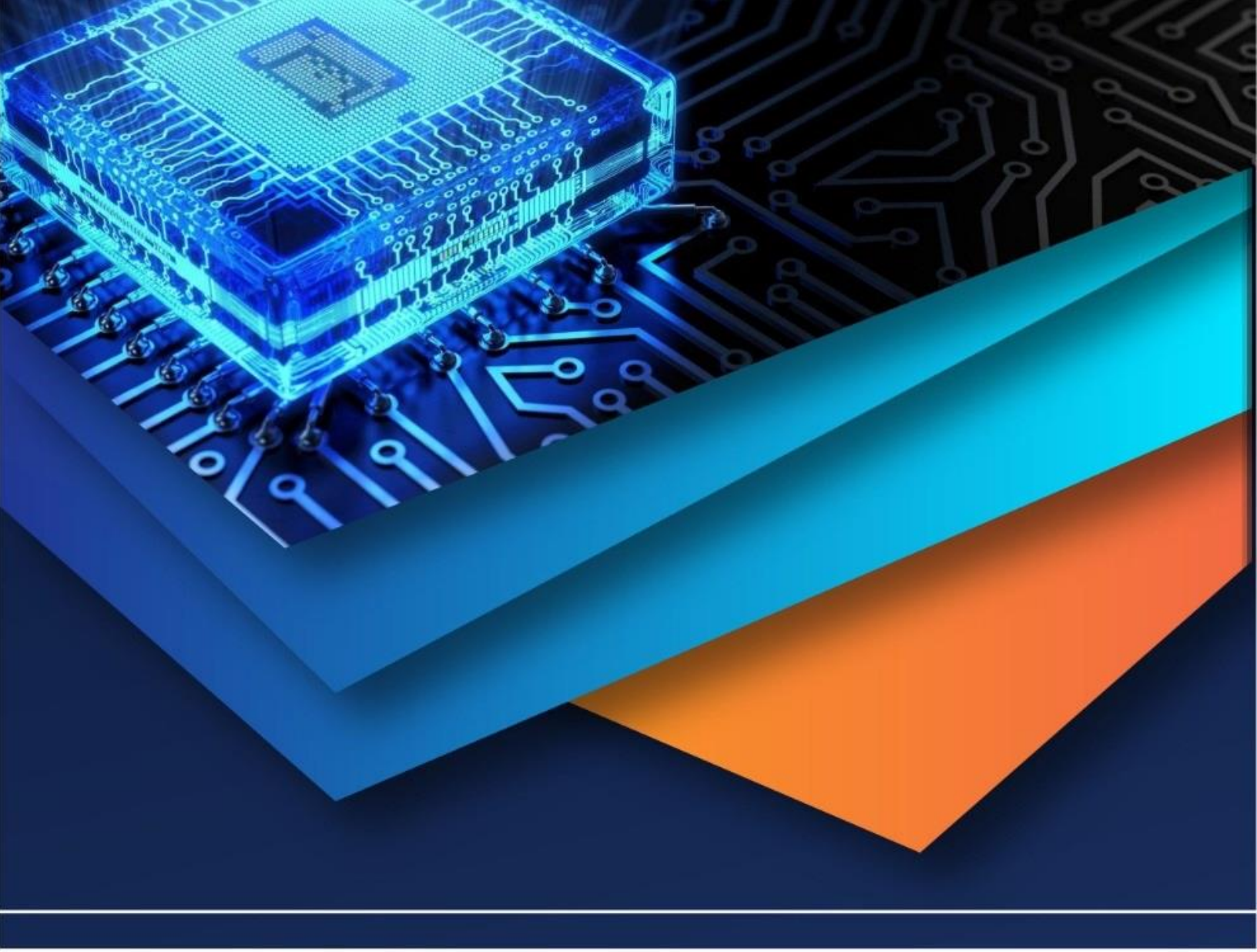
[10] Z. Gao, J. Li, J. Guo, Y. Chen, Z. Yi and J. Zhong, "Diagnosis of Diabetic Retinopathy Using Deep Neural Networks," in IEEE Access, vol. 7, pp. 3360-3370, 2019.

[11] https://www.kaggle.com/benjaminwarner/resized-2015-2019-blindness-detection image

[12] K. Palavalasa and B. Sambaturu, "Automatic Diabetic Retinopathy Detection Using Digital Image Processing," 2018 International Conference on Communication and Signal Processing (ICCSP),Chennai, India, 2018, pp. 0072-0076

[13] K. S. Argade, K. A. Deshmukh, M. M. Narkhede, N. N. Sonawane and S. Jore, "Automatic detection of diabetic retinopathy using image processing and data mining techniques," 2015 International Conference on Green Computing and Internet of Things (ICGCIoT), Greater Noida, India, 2015, pp. 517-521

[14] X. Zeng, H. Chen, Y. Luo and W. Ye, "Automated Diabetic Retinopathy Detection Based on Binocular Siamese-Like Convolutional Neural Network," in IEEE Access, vol. 7, pp. 30744-30753,



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY