Indonesian Journal of Electrical Engineering and Computer Science
Vol. 24, No. 1, October 2021, pp. 208~216
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v24.i1.pp208-216

Diabetic retinopathy classification using deep convolutional neural network

Akshita L, Harshul Singhal, Ishita Dwivedi, Poonam Ghuli
Department of Computer Science Engineering, RV College of Engineering, India

Article Info

Article history:

Received Jun 7, 2021
Revised Aug 4, 2021
Accepted Aug 11, 2021

Keywords:

Deep CNN
Histogram equalization
Image processing retinopathy
Segmentation

ABSTRACT

Diabetic retinopathy (DR) is a diabetic impairment that affects the eyes and if not treated could lead to permanent vision impairment. Traditionally, Ophthalmologists perform diagnosis of DR by checking for existence and any seriousness of some subtle features in the fundus images. This process is not very efficient as it takes a lot of time and resources. DR testing of all the patients, a lot of which are undiagnosed or untreated, is a big task due to the inefficiency of the traditional method. This paper was written with the aim to propose a classification system based on an efficient deep convolution neural network (DCNN) model which is computationally efficient. Amongst other supervised algorithms involved, proposed solution is to find a way to efficiently classify the fundus images into 5 different levels of severity. Application of segmentation after the pre-processing and then use of deep convolutional neural networks on the dataset results in a high accuracy of 91.52%. The result achieved is high given the limitations of the dataset and computational powers.

Corresponding Author:

Poonam Ghuli
Department of Computer Science and Engineering
RV College of Engineering
Bengaluru, Karnataka, 560059, India
Email: poonamghuli@rvce.edu.in

1. INTRODUCTION

Diabetic melitus (DM) is a chronic disease that affects nearly 400 million patients worldwide and is expected to increase to 600 million adults by 2035. Patients affected by DM can develop other diseases derived from diabetes. The most serious DM ocular derived disease is diabetic retinopathy (DR) [1]. It is caused by high levels of blood sugar because of diabetes. Over time the retina. the part of a person's eye which is responsible for detecting light and sending signals to their brain through the optic nerve (which is at the back of the eye). is damaged due to having too much sugar in the body. Blood vessels in the entire body are damaged due to diabetes. So when sugar becomes excessive in the body, the blood vessels that go to the retina are blocked and this causes them to bleed and leak fluid. The eye tries to grow new blood vessels to make up for these blocked blood vessels but they can bleed or leak fluids easily as they don't work as well [2].

The obvious symptoms don't usually occur in the early stages of the disease. Common eye complications like seeing faraway objects or even trouble reading, which come and go. It is only in the later stages, when the retinal blood vessels leak into the vitreous, that dark, floating spots are visible. Diabetic retinopathy is considered as the most common cause of blindness which can be prevented in the working age population in most countries [3]. Physicians use retinal image analysis for eye screening to detect disease-related lesions. Manually analysing all the images is becoming excessively unaffordable due to the number of diabetic people increasing at a fast pace. Since the process of image-based diagnosis requires personnel who have expertise in the field and training them to gain expertise requires daily practice, there is a shortage of such personnel [4].

Disease detection using non-mydriatic fundus cameras results to be a very cost-effective method for DR screening [5]. Design of automatic diagnostic systems for medical imaging generally and for DR particularly, could help reduce the prevalence of most severe disease cases, increase the cost effectiveness of diagnostic systems, reduce its associated costs and increase patient's life. In [6], a review on feature extraction is conducted. These techniques have been applied to get components of the image which will reduce redundant data and that can be helpful in the classification and in recognizing images. This paper specifically shows its working in a character recognition system. Various types of features, and their techniques to extract features as well as understanding the technique which is best suited for a particular situation. In [7], feature extraction and image processing concepts and its basic operations have been highlighted. It provides working implementations of major feature extraction techniques to be applied in the process of selection of imagery. It further explains low level and high-level techniques for feature extraction. It also gives an introductory explanation to pattern classification.

In [8], development of a customized CNN architecture has been proposed for DR images which consists of 5 layers, 3 fully connected neural layers and 2 convolution layers. Along with this, pre-trained models SqueezeNet, VGG-16 and AlexNet were also implemented to compare the results. The pre-trained models fell short when compared to the customized architecture in terms of accuracy, sensitivity and specificity. In [9], another paper which focuses on segmentation and then detection and classification of the disease into 5 different levels of severity through various pre-trained models has been reviewed. Data normalization and augmentation was performed to compensate for the lack of retinal image defects. The model VggNet was found to have better performance as compared to AlexNet, GoogleNet and ResNet.

In [10], a deeply-supervised pre-trained CNN model was implemented. The pre-trained model used for this purpose was ResNet which contains 11 layers. In intermediate hidden layers of this ResNet model, additional side-output layers were added. These additional layers were added to learn classification features at a certain scale and produce additional regularization. In [11], the study shows the use of TensorFlow for classification of data with deep learning. Multiple activation functions were studied and compared to see their effects on classification results. ReLU, eLu, tanH, softplus, sigmoid and softsign functions were used for this purpose. Softmax and CNN Classifier were used as deep learning models. The ReLU activation function was found to have the most accurate classification rate. In [12], the proposed system is a CNN based model in order to detect diabetic retinopathy using digital retinal images and classify them based on severity. For identification of features such as micro-aneurysms, exudate and hemorrhages, a network with data augmentation and CNN is applied. The accuracy obtained was about 75% with 95% sensitivity during validation. In [13], the long-term effects of various types of DR and diabetes are discussed. The study shows that persons with type 1 diabetes are prone to be affected by DR compared to persons with type 2 diabetes. The DR being sight-threatening and non-sight-threatening changes based on how long the person is affected by diabetes. About 94% of the population in Wales between 2005 to 2009 were screened.

In [14], a deep learning algorithm-based technique is used for diabetic retinopathy classification. This method had high sensitivity and specificity to detect DR. It provides several advantages such as consistency of interpretation, high sensitivity and instantaneous report generation. The algorithm is trained to also identify diabetic macular edema. In [15], the proposed system makes use of a unique CNN model for feature extraction from the input images. The evaluation of the model is done using various machine learning classifiers like J48, Random Forest, Naive Bayes, AdaBoost and support vector machines. According to the evaluation result, the J48 classifier with feature extraction technique proves to be the best.

In [16], the proposed system implements a synergic deep learning model for the diabetic retinopathy classification. It starts with preprocessing of the dataset followed by segmentation based on histogram to extract useful regions. The Messidor DR dataset was used and the SDL model was used on in. The accuracy, sensitivity and specificity of 99.2, 98.5 and 99.3 respectively was shown by the model that proved to be an excellent classification model. In [17], the proposed system uses a DNN with a moth search optimization algorithm for detection and classification of DR images. The contrast limited adaptive histogram equalisation model is used on the DR images followed by segmentation using histogram approach. Feature extraction is completed by using Inception-ResNet V2 model and the extracted features are fed as input to the classifier model based on DNN-MSO to classify the level of damage caused by DR.

In [18], a review on the analysis of the existence of diabetic retinopathy with the help of an ensemble of machine learning algorithms which work on the output of feature extraction on retinal images for classification. It uses various algorithms like random forest, SVM and alternating decision trees. It also compares the accuracy of various combinations of the algorithms. In [19], an automated deep learning algorithm driven by data is used for grading the severity of DR. A panel of actual professionals were approached for determining the actual severity of the training dataset used for the model and checking the accuracy.

In [20], the model uses a Gabor filter for enhancing the retinal images. A mathematical morphological based segmentation is done on the images. The feature extraction helps in classifying the images with exudates and images without exudates. The validation is done by comparing the result with the already existing datasets. In [21], the proposed system includes densely and deeply connected networks for the analysis of images of the retina in order to train the network. The accuracy is enhanced as the CNN layers are dense and deeply connected. The growth rate also helps the model in learning the delicate features of the dataset images used at every stage in the given network.

In [22], the following system works on the dataset used from the UCI machine learning repository that is first normalized with the help of standard scalar technique followed by extraction of significant features through principal component analysis (PCA) and for dimensionality reduction the Firefly algorithm is used. The final reduced dataset is used as input for the DNN Model that helps in classification. The result, which is specified with the help of metrics like specificity, sensitivity, accuracy, precision, and recall, states the greater efficiency of the proposed model over the existing machine learning models.

The motivation of this thesis is the exploration of new and effective methods for the diabetic retinopathy disease detection, classification and lesion detection through automatic analysis of retina fundus images. In this paper we have proposed a computationally efficient deep convolution neural network (DCNN) model which takes segmented image obtained and trains it to classify a retinal image into 5 categories of diabetic retinopathy based on severity. The five categories are: Normal (No DR), mild, moderate severe and proliferate [23].

2. RESEARCH METHOD

The proposed system includes an automated knowledge model to identify the existence of diabetic retinopathy. As seen in Figure 1, the model has been trained with backpropagation NN and convolutional neural network by testing their accuracy with CPU trained neural networks. The testing is done with deep neural network as it obtains performance which is superior to that of NN. The images in the dataset are preprocessed with a set of steps which include histogram equalisation in order to improve the accuracy of the model.

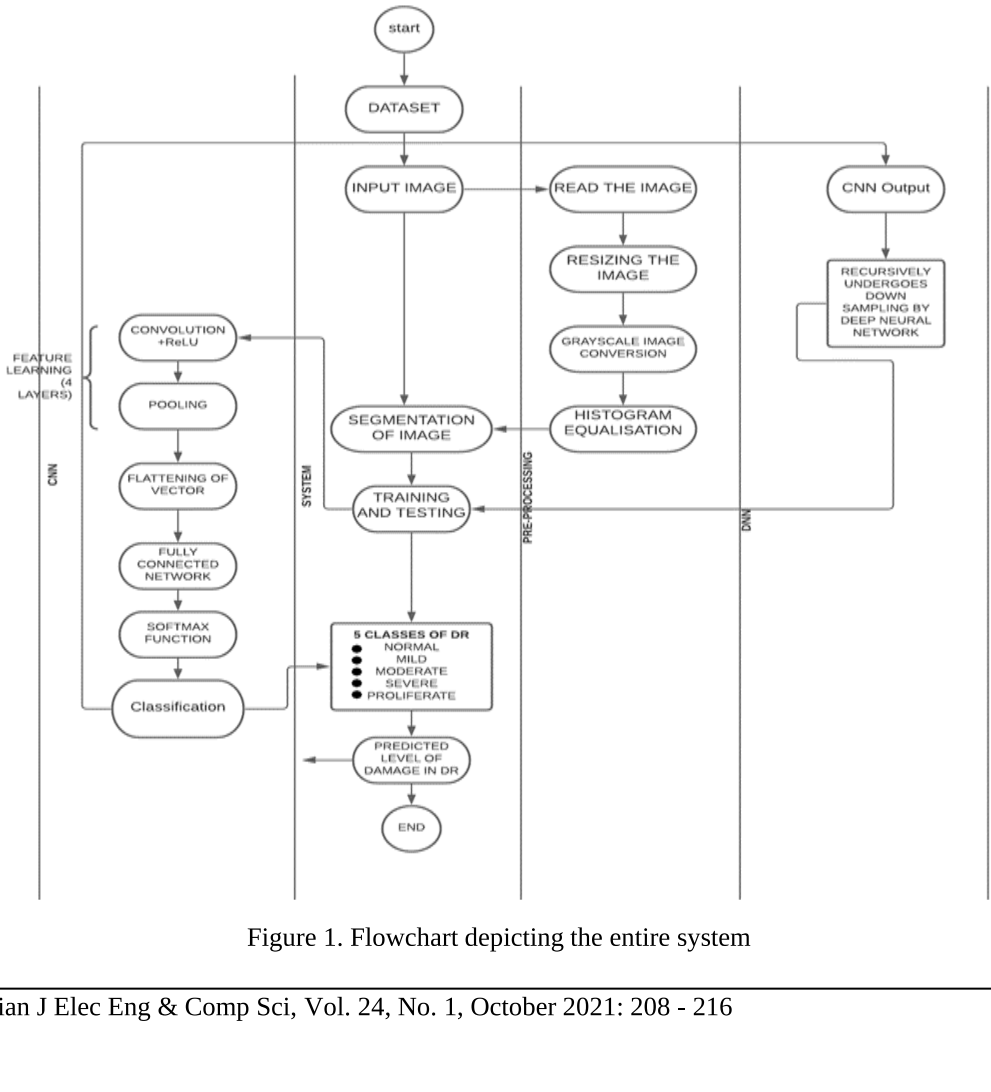


Figure 1. Flowchart depicting the entire system

2.1. Dataset creation

The data for the model is a large dataset of images which are obtained from the EyePACS dataset sponsored by California Healthcare foundation. It consists of around 17,540 colour retinal images which are to be classified into five categories. The model uses 80% for training and 20% for testing. Figure 2 shows examples of the retinal images used.

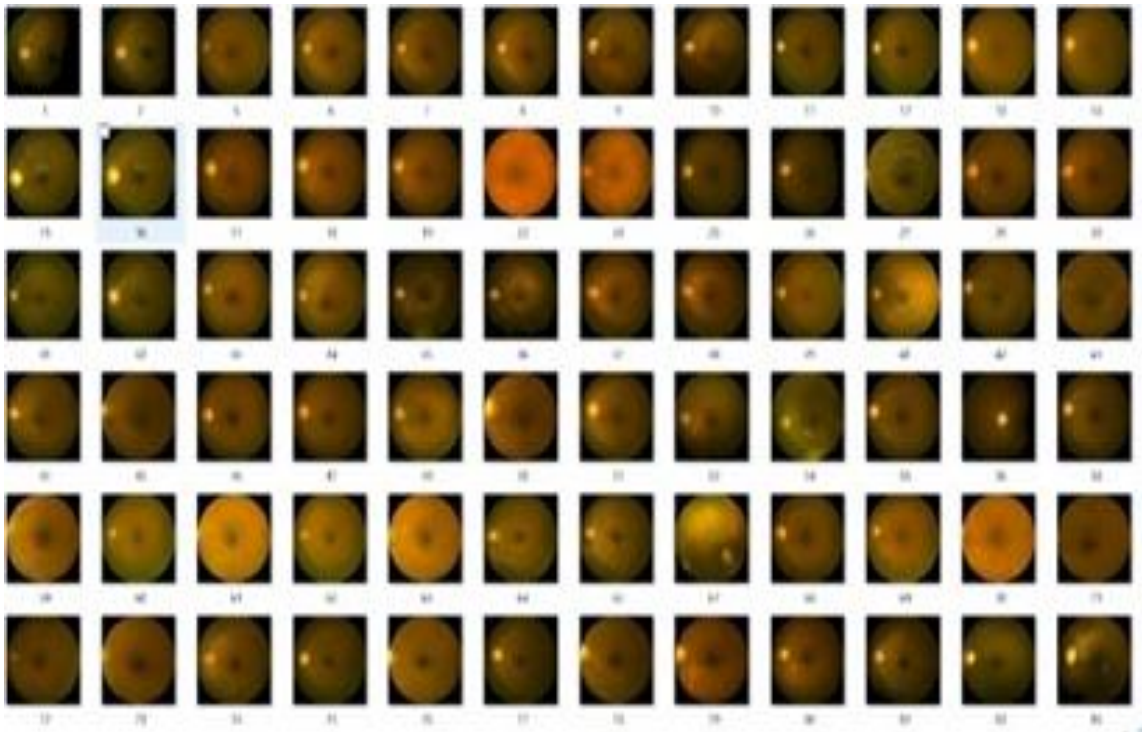


Figure 2. Dataset of retinal images

2.2. Preprocessing with histogram equalisation

Histogram equalisation is a contrast enhancement method to improve the standard of the image for better classification. It spreads out the intensity of the most frequent pixel and stretches out the intensity range of the image [24].

2.3. Prerequisite for conversion

An image can be of any size but they all need to be of the same size for this algorithm to work. All images are resized to a size of 250x250. The images are to be converted to grayscale images for better color balance. Histogram equalisation is done with the help of *cumulative distribution function* which uses *p(x) which* is the image's histogram for each pixel. The function is shown in (1). Figure 3 shows the image obtained after Histogram equalisation (1). Equation for obtaining normalized histogram.

$$cdf_x(i) = \sum_{j=0}^{i} p_x(x = j) \quad (1)$$

2.4. Segmentation

Segmentation is the process of splitting the image into multiple segments i.e., set of pixels in order to simplify the representation for easier analysis. In this process the pixels with similar characteristics share the same labels [25]. This process helps in isolating the diseased area in the retinal images such that they can be classified into different levels based on severity. It uses edge detection in order to extract a set of contours which helps in classification. Figure 4 shows the image after segmentation.

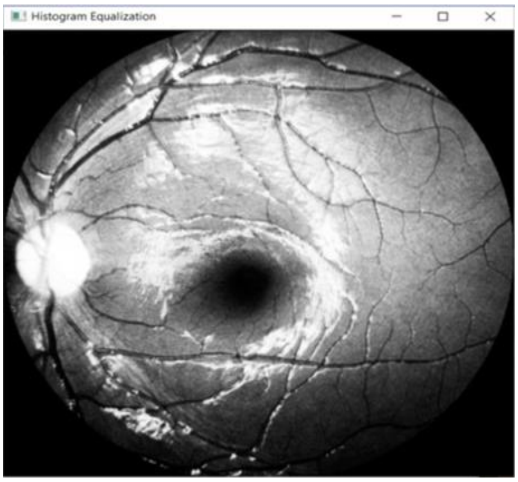


Figure 3. Image after histogram equalisation

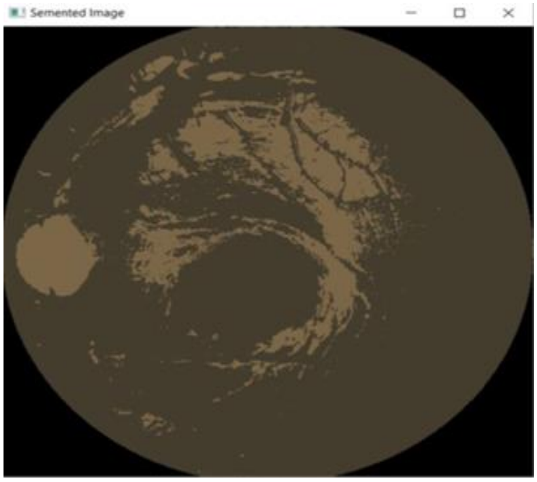


Figure 4. Segmented image

2.5. Training

Convolutional neural network (CNN) which is one of the most prevalent algorithms for deep learning has been used for training the model using five different classes-normal, mild, moderate, severe and proliferate in order to classify the diabetic retinopathy images accordingly. A bunch of Images including the target is given as the input to train the CNN model that includes mainly two kinds of layers for Feature Learning:

1. Convolution layer and rectilinear layer
   The Convolution filter helps in edge detection of the diseased area in the image with background and foreground filtering. Rectilinear is another filter that is used for downsampling images that helps in reducing the pixels of the images.
2. Pooling layer
   In this layer the target images are assigned the target value called label.

The proposed model is trained using 4 such layers repeatedly. Following processes are used for classification:

- Flattening: Converts the matrix obtained to single array features.
- Fully Connected Layer: This layer helps in connecting input with the correct target.
- Softmax: This helps in assigning features corresponding to the labels to provide the lassification output.
- The model is trained recursively in order to achieve better accuracy.

2.6. Testing

This step is the final step used to test the model in which a given retinal test image is selected that undergoes preprocessing and segmentation followed by the CNN layers that classifies the image and predicts the level of damage in the given retinal test image and displays the original image, black and white form of the test image, histogram equalised form of the image and segmented image to display the diseased area.

3. RESULTS AND DISCUSSION

The dataset used is divided into three parts for training, testing and validation dataset where training dataset is used to train the model, validation dataset is used at the development stage of model to give an unbiased estimate of the final tuned model and testing dataset used to access the final model.

3.1. Segmentation of the dataset

Original retinal images are read from the dataset which are then converted to black and white images that are further enhanced with the help of histogram equalisation followed by segmentation. The segmented images are stored in new folders depending on the level of damage classified for each image.

3.2. Training of the model

This step is used to train the model so that it can understand the previous patterns for better performance in order to make the ability to predict the level of damage more accurate. Training starts by setting the number of epochs which is the number for training the neural network with all training data for one cycle. After the training of the model is completed, the accuracy metric, that states the proportion of correct predictions, is displayed along with the accuracy curve that shows the progress in the neural network [26].

The accuracy for 1000 epochs was seen to be 91.525 by the model and hence observed that accuracy increased as the number of epochs increased. Figure 5 shows the model accuracy graph for 50 epochs.

The loss curve is an important graph that gives the direction in which the neural network learns and states the learning rate. It displays the distance between true values of the problem and the predicted values of the model. Good learning rate is observed when the loss values decrease and become stable at one point as the epochs increase. The loss curve for 50 epochs is shown in Figure 6.

The receiver operating characteristic (ROC) curve is the graph that shows the relationship between true positive rate and false positive rate and evaluates the working of a classification model at all thresholds. The ROC curve for 50 epochs is shown in Figure 7. Confusion matrix is a table that shows the performance of a classification model by displaying the number of correct values predicted and incorrect values predicted per class on the set of test data for which the correct values are already known [27]. Figure 8 shows the confusion matrix and accuracy for 1000 epochs. Table 1 shows the number of true and false positive values for 472 images which is used for calculation of accuracy.

Accuracy = (TP+TN)/(TP+TN+FP+FN)

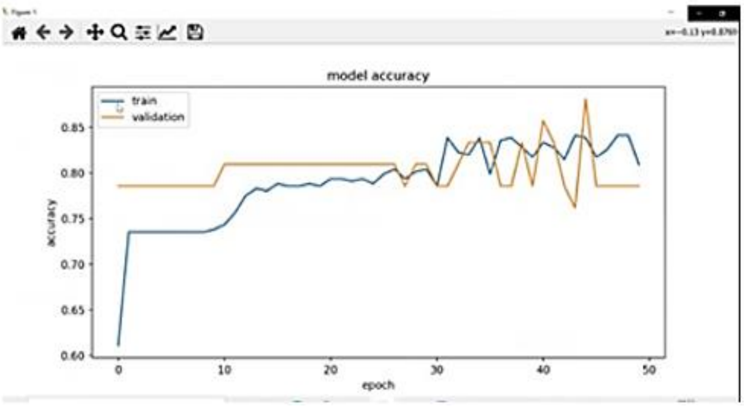


Figure 5. The model accuracy graph shown for 50 epochs has less gap between validation and training suggests that the model is not overfitted

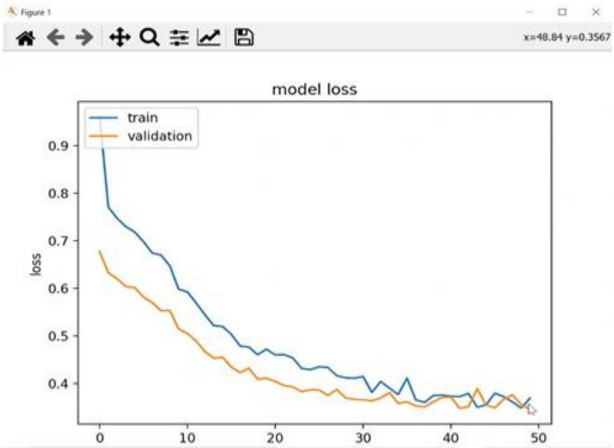


Figure 6. Loss graph to check the loss encountered during training and validation shows loss value going down with increase in epoch

Table1. Calculation of accuracy of the model using confusion matrix for 1000 epochs

Class	No. of True Positive values	No. of False Positive values	Total number of Images class wise
1	20	0	20
2	85	4	89
3	301	10	311
4	6	8	14
5	20	18	38
Total	432	40	472

Total Number of True Positive values= 432. Total Number of Test Images= 472. Since, Accuracy= True Positive/ (True Positive + False Positive) Therefore, Accuracy of the model= (432/472) *100 = 91.525%.

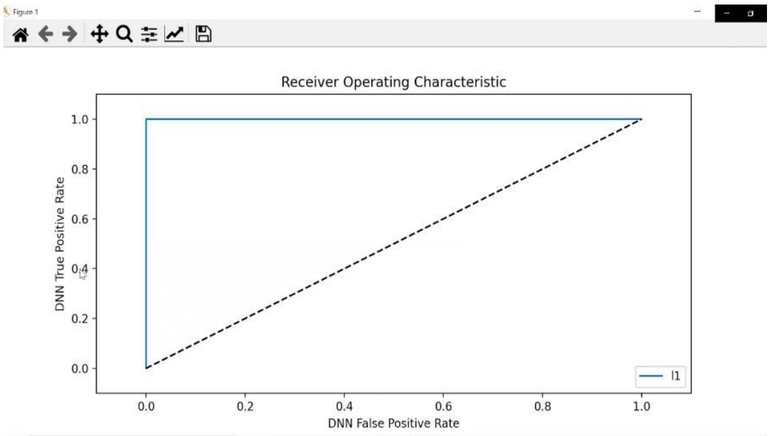


Figure 7. ROC curve predicts that the model is almost classified properly

```
SB_DNN confusion matrics= [[ 20   0   0   0   0]
 [  0  85   4   0   0]
 [  0   2 301   0   8]
 [  0   8   0   6   0]
 [  0   0  18   0  20]]

SB_DNN accuracy= 91.52542372881356
```

Figure 8. Accuracy and confusion matrix for 1000 epochs

3.3. Testing of the model

In the following part the model is checked by giving a retinal test image as the input which is preprocessed by the model using histogram equalisation technique followed by segmentation where segmented image is saved in the png format and given as an input to pathtotensor that converts image into features which helps the model to classify and predict the correct level of damage in the retinal image. It also displays the original test image, black and white form of the image, histogram equalised form of the image and segmented version of the image. Figure 9 shows the prediction made by the model for a random retinal image along with all the images generated in the process.

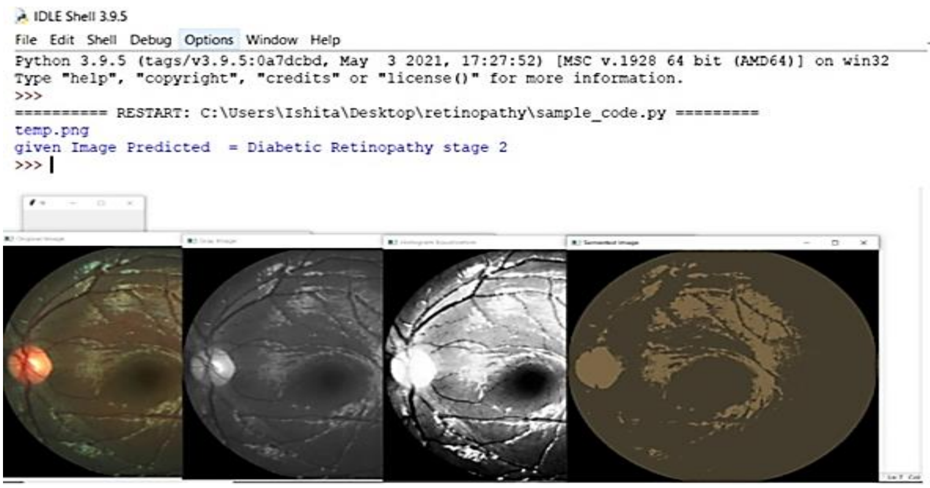


Figure 9. The final output predicts the damage level due to DR in the selected test image and displays the original image, black and white image, histogram equalized image and segmented test image

4. CONCLUSION

The proposed system is an effective diabetic retinopathy automated classification system based on a algorithmically coherent CNN model that is deeply trained and uses histogram equalisation as a preprocessing technique to enhance the features of the retinal image followed by segmentation to display the diseased area in the retinal image that helps in predicting the damage level caused by DR. The model uses a deeply connected convolutional neural network with 4 layers in each iteration. The accuracy obtained in the model is 91.52% on 1000 epochs and was further observed that the accuracy increases as the number of epochs increases. The given models covered a relatively small dataset and hence can be extended by applying it on a much larger dataset which would help in training the model with lesser iterations and improve the accuracy for testing. Further the proposed system can be deployed to complex platforms such as mobile phones or field programmable gate array devices.

REFERENCES

[1] Zheng, Y., He, M. and Congdon, N., “The worldwide epidemic of diabetic retinopathy,” *Indian Journal of Ophthalmology*, vol. 60, no. 5, pp. 428-431, 2012, doi: 10.4103/0301-4738.100542.

[2] “Diabetic Retinopathy,” [Online] Available: https://www.nei.nih.gov/learn-about-eye-health/eye-conditions-and-iseases/diabetic-retinopathy, [Accessed: 2021-05-29].

[3] Lee, R., Wong, T. Y., and Sabanayagam, C., “Epidemiology of diabetic retinopathy, diabetic macular edema and related vision loss,” *Eye and Vision*, vol. 2, no. 1, pp. 1-25, 2015, DOI: 10.1186/s40662-015-0026-2.

[4] De La Torre, J., Valls, A. and Puig, D., "Diabetic retinopathy detection through image analysis using deep convolutional neural networks,” *19th International Conference of AI Research and Development, IOS press*, 2016, pp. 58-63, doi: 10.3233/978-1-61499-696-5-58.

[5] Fahadullah, M., *et al*., “Diagnostic accuracy of non-mydriatic fundus camera for screening of diabetic retinopathy: A hospital based observational study in Pakistan,” *Journal of the Pakistan Medical Association*, vol. 69, no. 3, pp. 378-382, 2019.

[6] Kumar, G. and Bhatia, P. K., "A Detailed Review of Feature Extraction in Image Processing Systems," *IEEE Fourth International Conference on Advanced Computing & Communication Technologies*, Rohtak, 2014, pp. 5-12, doi: 10.1109/ACCT.2014.74.

[7] Nixon, M. S., and A. S. Aguado, “Low-level feature extraction (including edge detection)," *Feature Extraction and Image Processing. 3rd edi. Linacre House/Jordan Hill/Oxford: Elsevie*, 2008, pp. 115-79, doi: 10.1016/B978-0-12-396549-3.00004-5.

[8] Khan, S.H., Abbas, Z. and Rizvi, S.D., “Classification of Diabetic Retinopathy Images Based on Customized CNN Architecture,” *Amity Int. Conf. on Artificial Intelligence*, 2019, pp. 244-248, doi: 10.1109/AICAI.2019.8701231.

[9] Wan, S., Liang, Y. and Zhang, Y., “Deep convolutional neural networks for diabetic retinopathy detection by image classification,” *Comp. Elec. Eng.*, vol. 72, pp. 274-282, 2018, doi: 10.1016/j.compeleceng.2018.07.042.

[10] Zhang, Debiao, Wei Bu, and Xiangqian Wu, “Diabetic retinopathy classification using Deeply Supervised ResNet,” *IEEE Smart World, Ubiquitous Intelligence & Computing, Advanced & Trusted Computed, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation*, pp. 1-6, 2017, doi: 10.1109/UIC-ATC.2017.8397469.

[11] Ertam, F. and Aydın, G., "Data classification with deep learning using Tensorflow," *2017 International Conference on Computer Science and Engineering (UBMK)*, pp. 755-758, 2017, doi: 10.1109/UBMK.2017.8093521.

[12] Pratt, H., Coenen, F., Broadbent, D.M., Harding, S.P. and Zheng, Y., “Convolutional Neural Networks for Diabetic Retinopathy,” *Procedia Computer Science*, vol. 90, no. 1, pp. 200-205, 2016, doi: 10.1016/j.procs.2016.07.014.

[13] Thomas, R. L., *et al., “*Prevalence of diabetic retinopathy within a national diabetic retinopathy screening service,” *British Journal of Ophthalmology*, vol. 99, no. 1, pp. 64-68, 2015, doi: 10.1136/bjophthalmol-2013-304017.

[14] Gulshan, V. *et al.*, “Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs,” *JAMA*, vol. 316, no. 22, pp. 2402-2410, 2016, doi: 10.1001/jama.2016.17216.

[15] Gayathri, S., Varun P. Gopi, and Ponnusamy P., “A lightweight CNN for Diabetic Retinopathy classification from fundus images,” *Biomed. Sig. Pro. Con.*, vol. 62, pp. 102-115, 2020, doi: 10.1016/j.bspc.2020.102115.

[16] Shankar, K., Sait, A. R. W., Gupta, D., Lakshmanaprabu, S. K., Khanna, A. and Pandey, H. M., “Automated Detection and Classification of Fundus Diabetic Retinopathy Images using Synergic Deep Learning Model,” *Pattern Recognition Letters*, vol. 133, no. 1, pp. 210-216, 2020, doi: 10.1016/j.patrec.2020.02.026.

[17] Shankar, K., Perumal, E. and Vidhyavathi, R. M., "Deep neural network with moth search optimization algorithm based detection and classification of diabetic retinopathy images," *SN Applied Science*, vol. 2, no. 4, pp. 1-10, 2020, doi: 10.1007/s42452-020-2568-8.

[18] Bhatia, K., Arora, S. and Tomar, R, "Diagnosis of diabetic retinopathy using machine learning classification algorithm," *2nd IEEE International Conference on Next Generation Computing Technologies (NGCT)*, Dehradun, India, pp. 347-351, 2016, doi: 10.1109/NGCT.2016.7877439.

[19] Gargeya, R. and Leng, T., “Automated Identification of Diabetic Retinopathy Using Deep Learning,” *Ophthalmology*, vol. 124, no. 7, pp. 962-969, 2017, doi: 10.1016/j.ophtha.2017.02.008.

[20] Reddy, G. T. *et al.*, “An Ensemble based Machine Learning model for Diabetic Retinopathy Classification,” *International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE)*, pp. 1-6, 2020, doi: 10.1109/ic-ETITE47903.2020.235.

[21] Riaz, H., Park, J., Choi, H., Kim, H. and Kim, J., "Deep and Densely Connected Networks for Classification of Diabetic Retinopathy Diagnostics," *Diagnostics Journal*, vol. 10, no. 1, pp. 24-30, 2020, doi: 10.3390/diagnostics10010024.

[22] Gadekallu, T. R. *et al.*, "Early Detection of Diabetic Retinopathy Using PCA-Firefly Based Deep Learning Model," *Electronics Journal*, vol. 9, no. 2, pp. 274-280, 2020, doi: 10.3390/electronics9020274.

[23] Alyoubi, W. L., Shalash, W. M. and Abulkhair, M. F., "Diabetic retinopathy detection through deep learning techniques: A review. Informatics in Medicine Unlocked," vol. 20, p. 100377, 2020, doi: 10.1016/j.imu.2020.100377.

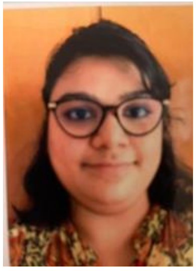
[24] Bagade, S. S. and Shandilya, V. K., "Use of Histogram Equalization in Image Processing for Image Enhancement," *International Journal of Software Engineering Research & Practices*, vol. 1, no. 2, pp. 6-10, 2011.

[25] Al Saleh, S., Kalyankar, N. V. and Khamitkar, S. D., "Image Segmentation by Using Threshold Techniques," *Journal of Computing*, vol. 2, no. 5, pp. 2151-9617, 2010.

[26] Shankar, K., Zhang, Y., Liu, Y., Wu, L. and Chen, C. H., "Hyperparameter Tuning Deep Learning for Diabetic Retinopathy Fundus Image Classification," *IEEE Access*, vol. 8, pp. 118164-118173, 2020, doi: 10.1109/ACCESS.2020.3005152.

[27] Ali, A. *et al*., "Machine Learning Based Automated Segmentation and Hybrid Feature Analysis for Diabetic Retinopathy Classification Using Fundus Image," *Entropy Journal*, vol. 22, no. 5, pp. 567-572, 2020, doi: 10.3390/e22050567

BIOGRAPHIES OF AUTHORS



Akshita L. is a 4th year student in the department of Computer Science and Engineering, RV College of Engineering. Her research interests are in the area of Data Analytics and Deep Learning.

Harshul Singhal is a 4th year student in the Department of Computer Science and Engineering, RV College of Engineering, Bengaluru, Karnataka, India. His research interests are in the area of Artificial Intelligence and Deep Learning.

Ishita Dwivedi is a 4th year student in the Department of Computer Science and Engineering, RV College of Engineering, Bengaluru, Karnataka, India. Her research interests are in the area of Data mining.

Dr. Poonam Ghuli is an Associate Professor at the Department of Computer Science and Engineering, RV College of Engineering, Bengaluru. She has completed her PhD in the area of Machine Learning from Visvesvaraya Technological University, Karnataka, India in the year 2017. Her research interests are Data Analytics, Machine Learning and Computer Vision. She is actively involved in research and consultancy work supported by many leading industries.