

PAPER • OPEN ACCESS

Detection of diabetic retinopathy using deep learning methodology

To cite this article: Gazala Mushtaq and Farheen Siddiqui 2021 *IOP Conf. Ser.: Mater. Sci. Eng.* **1070** 012049

View the [article online](#) for updates and enhancements.

You may also like

- [An Empirical Exploration of Artificial Intelligence in Medical Domain for Prediction and Analysis of Diabetic Retinopathy: Review](#)
S V Deshmukh and A Roy
- [Categorization of Diabetic Retinopathy using Deep Learning Techniques](#)
N T Renukadevi, K Saraswathi, S Karunakaran et al.
- [Blood vessel segmentation for diabetic retinopathy](#)
Arun T Nair, Dr. K Muthuvel and K S Haritha

Detection of diabetic retinopathy using deep learning methodology

* **Gazala Mushtaq**¹ and **Farheen Siddiqui**²

Department of Computer Science and Engineering, School of Engineering Sciences and Technology, Jamia Hamdard, New Delhi-110062, India

¹*gazalamushtaq188@gmail.com, ²fsiddiqui@jamiahamdard.ac.in

Abstract. Diabetic retinopathy is a complication of diabetes that targets the eyes by damaging the retinal blood vessels. Initially it is asymptomatic or causes fluctuating vision problems. As it becomes severe, it affects both the eyes and eventually causes partial or complete vision loss. Primarily occurs when the blood sugar level is unmanageable. Therefore, the person with diabetes mellitus is always at a high risk of acquiring this disease. The early detection can deter the contingency of complete and permanent blindness. Thus, requires an efficient screening system. The present work considers a deep learning methodology specifically a Densely Connected Convolutional Network DenseNet-169, which is applied for the early detection of diabetic retinopathy. It classifies the fundus images based on its severity levels as No DR, Mild, Moderate, Severe and Proliferative DR. The datasets that are taken into consideration are Diabetic Retinopathy Detection 2015 and Aptos 2019 Blindness Detection which are both obtained from Kaggle. The proposed method is accomplished through various steps: Data Collection, Preprocessing, Augmentation and modelling. Our proposed model achieved 90% of accuracy. The Regression model was also employed, manifested up an accuracy of 78%. The main aim of this work is to develop a robust system for detecting DR automatically.

1. Introduction

Diabetes is one of the most common diseases and its prevalence has increased worldwide. It is primarily associated with the production of insulin and high blood sugar of the body[1] resulting in the anomalous metabolic functions and complications like cardiovascular diseases, kidney failures, neural disorders and diabetic retinopathy (loss of vision), etc. Diabetic retinopathy is a crucial eye condition which results in loss of vision that cannot be reversed or corrected once experienced. The people who have a long history of diabetes are more prone to get afflicted with this disease, no matter whether a person is type1 or type2 diabetic, the probability of the disease increases as the age increases[2]. According to WHO, DR is an intense eye disease that requires urgent contemplation at an international level. According to a report, in India there are about 12,000 ophthalmologists for 60 million diabetics with eye disorder. The main reason for such an alarming number of patients is the result of the fact that mostly people are oblivious that they are suffering from this disorder. They also show insensitivity and an incautious attitude towards this disease. About 18% of people with diabetes are suffering from DR and the possibility of procurement of DR in a diabetic person is 25 times more than that of a healthier



one[3]. The detection of this disorder is difficult to diagnose at an initial stage, owing to the fact that it is asymptomatic or shows very mild symptoms thus leaves a person in oblivion and eventually leads to vision impairment. Thus to detect DR at an early stage is pivotal in averting the complexities of this disorder. The diagnostics of this illness requires the professionals and specialists with highly effective equipment's and techniques that foster the advancements in leveraging the prognosis of this condition.

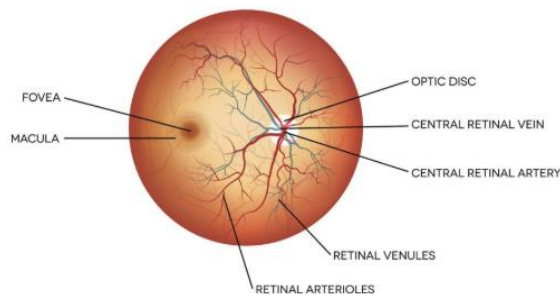


Figure 1. Normal Retina

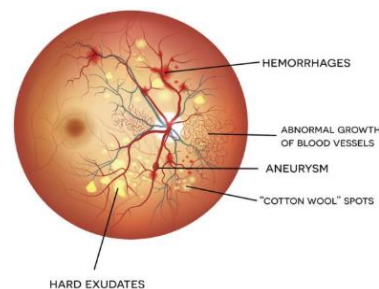


Figure 2. Diabetic Retinopathy

The image of normal retina and the Retina with Diabetic retinopathy is shown in figure 1 and figure 2 respectively[4]. Since an unerring automatic detection technique is required to classify and circumspect the severity level of DR. Mostly research in the area of DR was carried out on the basis of feature extraction using machine learning approaches, but the problem rose with the manual feature extraction which prompted researchers towards deep learning. The further research in medical fields paved path for many computer aided technologies like data mining, image processing, machine learning and deep learning. However, the Deep Learning has gained popularity in recent years in various fields like sentiment analysis, hand written recognition, stock market prediction and medical image analysis, etc. CNN in deep learning tends to provide constructive results when it come to the job of image classification. The architecture of CNN with its different layers is given in the figure 3[5].

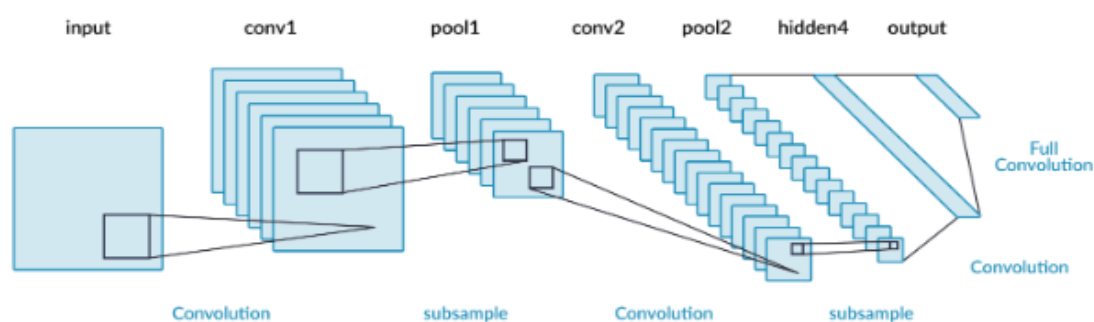


Figure 3. CNN Architecture

The present research employs deep learning methodology especially CNN variant DenseNet, which extracts the features automatically, rather than manually for the classification of fundus (eye) images based on the severity level. A Combination of the data set of “Diabetic Retinopathy Detection” 2015 from Kaggle and “Aptos 2019 Blindness Detection” from Kaggle was assembled for this study.

The paper is organized into various sections as: section 2 presents the recent work in this field. Section 3 gives the proposed solution for detecting DR. Section 4 will discuss the results of the research. Section 5 will provide a conclusion based on the research carried out in this study and finally Section 6 will conclude the paper by stating the limitation and future work for further study.

2. Related Work

Diabetic Retinopathy is one of the grave concerns that engrossed the whole world. Receiving the attention from various researchers in order to find the optimal solutions for the early detection of this disease, consequently leading to the prevention of premature fluctuations in vision. Many studies have been conducted and still continues in this field with an aim to ease the lives of both doctors as well as patients. This section provides a review of many research works in the area of Diabetic retinopathy.

J.calleja.et al [6] in their work used a two staged method for Diabetic retinopathy detection: LBP (Local Binary Patterns) for feature extraction and Machine Learning specifically SVM and Random Forest for classification purpose. The results obtained by the random forest outperformed the SVM with an accuracy of 97.46%. However, the dataset used in this study was quite small with 71 images.

Earlier works were based on manual feature extraction for detection of DR using various computer based systems. U.Acharya.et al[7] used features like blood vessels, microaneurysms, exudates, and haemorrhages from 331 fundus images using SVM with an accuracy of more than 85%. K. Anant.et al[8] in their literature used texture and wavelet features for DR detection by making use of data mining and image processing on a database DIARETDB1 and achieved 97.95% accuracy. M.Gandhi.et al[9] proposed a method for automatic DR detection with SVM classifier by detecting exudates from fundus images. Some works try to integrate manual feature extraction with deep learning feature extraction for DR. one of such work include J.Orlando.et al [10] where CNN with hand crafted feature are used for feature extraction for detecting red lesion in the retina of an eye.

S.Preetha et al.[11] In their literature predicted various diabetic related diseases using Data Mining and machine learning methods specifically for heart disease and skin cancer prediction while considering both advantages and disadvantages.

While many researches or works are there about using machine learning approaches or data mining approaches, a quite different approach also came into the way of detection of diabetic retinopathy. S.Sadda et al. [12] make use of quantative approach to identify new parameters for detecting proliferative diabetic retinopathy. It is based on the hypothesis that location, number and area of lesions can improve the forecasting process of Retinopathy. The methods used for this study were Subjects and Imaging Data, Ultrawide Field Image Lesion Segmentation, Quantitative Lesion Parameters and Statistical Analysis. Comparison of lesions were made on the basis of Lesion number, Lesion surface area, Lesion distance from the ONH center and Regression analysis. The work presented by J.Amin et al. [13] provides a review of various methodologies for diabetic retinopathy by detecting hemorrhages, microaneurysms, exudates and also blood vessels, and analyzes the various results obtained from theses methodologies experimentally in order to give indepth insight of ongoing research. The study carried out by Y.Kumaran and C.Patil [14] focuses on the different types of preprocessing and segmentation

techniques mostly and gives an in detail procedure for detection of diabetic retinopathy in human eye consisting of number of systems and classifiers. M.Chetoui et al.[15] Proposes a diagnostic method for DR using machine learning specifically SVM and Texture features. Texture features used were LTP (Local Ternary Pattern) and LESH (Local Energy-based Shape Histogram) that provided better results when compared to Local Binary Pattern (LBP). The accuracy of 90.4% was obtained by LESH with SVM.

Deep learning is the most popular approach among researchers for detection, prediction, forecasting and classification task in various fields from few years, in medical field particularly in diabetic retinopathy it is unveiling many possibilities for the prevention of such a dreadful disease. I.Sadek et al.[16] in their work automatically detected the diabetic retinopathy using deep learning approach. They used the four convolutional neural network to classify the diabetic retinopathy into three classes as Normal, Exudates, Drusen. This method outperforms the Bag of words approach and achieved an accuracy of 91%-92%. G.Zago et al.[17] in their study designed a lesion localization model using a deep network specifically convolutional neural network approach with an aim to address the models complexity so, that the performance can be improved. Instead of segmentation localization process of regions were used. Two convolutional networks were used for training purpose on a Standard Diabetic Retinopathy Database and DIARETDB1 where 94% - 95% of sensitivity was obtained. D.Doshi et al.[18] in their work used a GPU based convolutional neural network to classify the retinal images severity level into 5 stages. This approach used 3 models of CNN architecture and an ensemble model of the three to evaluate the results on kappa metrics. The best result were achieved by ensembling method with a score of 0.3996. The work of P.Kaur et al.[19] Presents a Neural network technique for the classification of retinal images using MATLAB. The results obtained were compared with the machine learning approach like SVM where better results were achieved. M.Voets et al.[20] in their study used a kaggle dataset EyePACS for detection of diabetic retinopathy from retinal fundus images. However, this study is the re-implementation of already existing work but on different data set which provided 95% of AUC. The difference of AUC between the original and the re-implemented method tend to be very large

3. Proposed 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). Many processes were carried out before feeding the images to the network. We trained two models in this work: our proposed model and the regression model and then a comparison was made between the accuracies obtained by the two models. Though our proposed model performed better than the regression model. The figure 4 shows the proposed methodology.

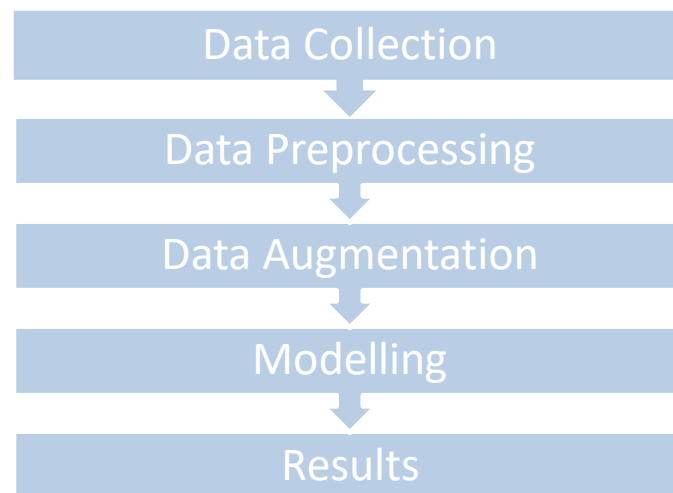


Figure 4 Proposed Methodology

3.1 Data Source: Data used for this study has been taken from Diabetic Retinopathy Detection 2015[21] and APTOS 2019 blindness detection[22] from kaggle. Both the datasets contains thousands of retinal images under different conditions. For every subject, two images of both the eyes are given as left and right. As the images come from different sources like different cameras, different models, etc. It has an abundance of noise associated with it, which apparently needs to be removed, thus, requiring a number of preprocessing steps. The diabetic retinopathy associated with each image has been rated on the scale of 0-4 as:

- 0 - No DR
- 1 - Mild
- 2 – Moderate
- 3 - Severe
- 4 - Proliferative DR

Figure 5 shows the retinal images with ratings on the basis of severity level from 0-1.

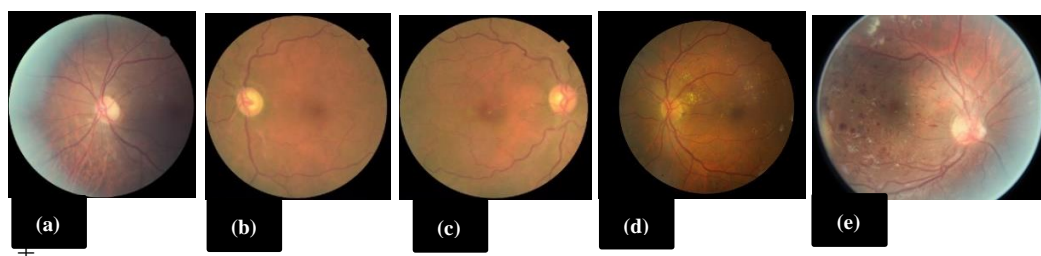


Figure 5 Image samples based on severity from dataset: (a) is level '0', (b) is level '1', (c) is level '2', (d) is level '3', (e) is level '4'.

3.2 Data Preprocessing As the images in the dataset contains a lot of noise, like some images may be out of focus, some may have a lot of exposure, some may have extra lighting, presence of the black background, etc. so we need to do preprocessing in order to get them in the standard format. Following things are carried out in preprocessing step:

- *Cutting the black border:* The black background of the fundus image does not add any information to the image and is therefore useless so, the black background around the images are omitted.
- *Remove the black corner:* After removing the black border there still exist some black corners as the fundus image is round in shape. In this step black corners are removed from the image.
- *Resizing image:* The images are resized to 256*256 (width*height).
- *Applying the Gaussian Blur:* Gaussian blur is applied to the images by specifying the kernel size to 256/6. This method helps in removing the Gaussian noise.

Figure 6 shows the images obtained after preprocessing was carried out.

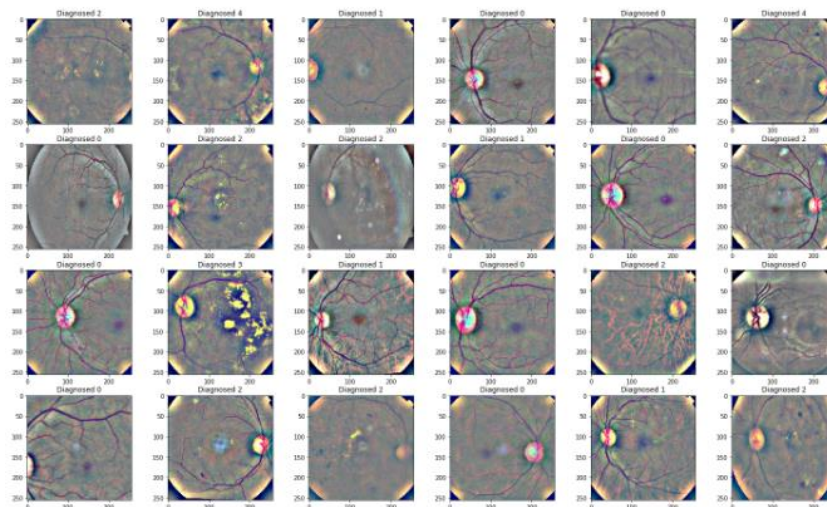


Figure 6 Images obtained after preprocessing.

3.3 Data Augmentation: After analyzing the data, we notice that the data is highly unbalanced among the diabetic retinopathy severity image classes as shown in figure 7, which gave rise to the propensity of data augmentation.

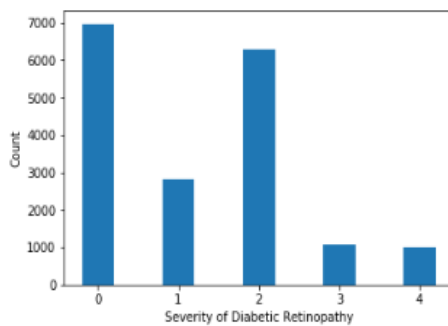


Figure 7 highly unbalanced data before data augmentation

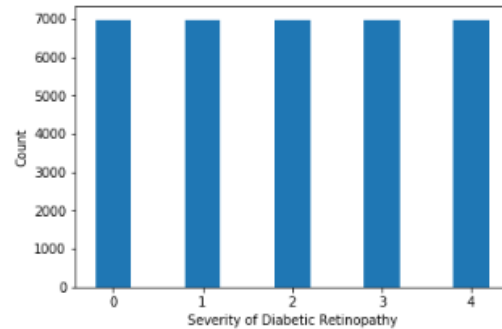


Figure 8 Balanced data after data augmentation

Data augmentation is framed by aligning one class to the class with most samples, in order to balance the data among the diabetic retinopathy severity classes, as shown in figure 8. Images were mirrored and rotated to augment the dataset, 7000 images were obtained in each class after augmentation shown in figure 9.

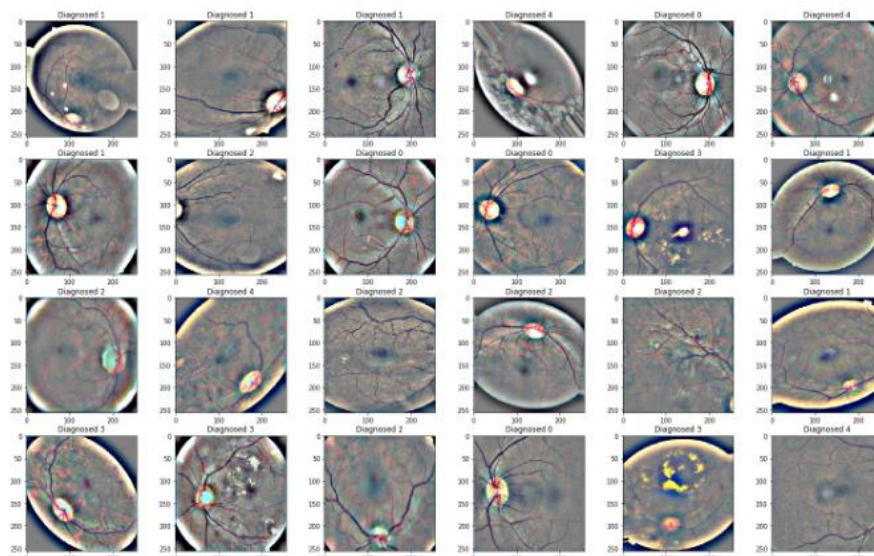


Figure 9 Images Obtained after Data Augmentation

3.4 Modelling: We used a DenseNet-169 (Densely connected convolutional neural network) and Regression model for training purpose. In DenseNet-169 weights are loaded into the network without the top or last layer. When modelling the network, initially there is no last layer. We design this layer by using Global Average Pooling 2D, a Dropout layer set at 0.5 and an output comprising of five nodes for each class. Global Average Pooling 2D is same as that of 2D average Pooling in operation, but it considers the entire input block size as pool size. A Dropout layer address the issue of over-fitting. Adam optimization algorithm is used for optimizing the weights on training this model. A sequential modelling approach is used for adding layers and customizing the layers like convolutional, dropout, dense, optimizers, etc.

Convolution layer: It employs several kernels or filters to run across the fundus images and calculate a dot product. Every kernel or filter in this layer draws various image characteristics

Pooling layer: It provides an abstract representation of convolved features by reducing the spatial dimension. It is somewhat similar to convolution layer but it takes the max or min region depends on the type of pooling from kernel-overlapped input.

Dropout layer: The dropout approach has been used to control neural networks in order to reduce over-fitting.

Flatten layer: Flattening transforms the data to the next layer in a 1-dimensional series.[23].

The figure 10 [24] shows the deep DenseNet-169 model with three Dense blocks and three transition layers consisting of pooling and convolution layer

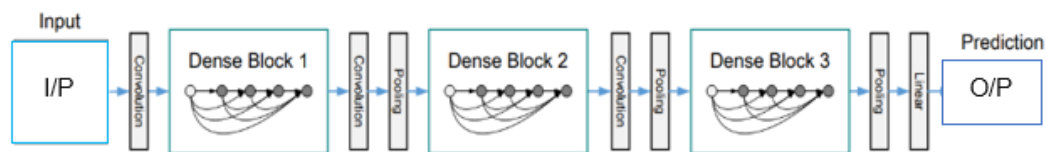


Figure 10 DenseNet-169 model with three dense blocks

```

Model: "sequential_1"
-----
Layer (type)                Output Shape          Param #
-----
densenet169 (Model)         (None, 8, 8, 1664)   12642880
-----
global_average_pooling2d_1 ( (None, 1664)         0
-----
dropout_1 (Dropout)         (None, 1664)         0
-----
dense_1 (Dense)              (None, 5)             8325
-----
Total params: 12,651,205
Trainable params: 12,492,805
Non-trainable params: 158,400
-----
None

```

Figure 11 summary of the model.

The summary of the model is given in figure 11. To stabilize the results a regression model was also used, which achieved an accuracy of 78%.

3.5 Implementation: The implementation was executed using python language, where a wide variety of libraries were employed for processing of images and to get acquainted with the system for creating convolutional neural network like DenseNet-169. The type of library utilized for image management (like rotation and resizing) and preprocessing was OpenCV[25]. However, the mathematical functions required for the implementation was performed by NumPy[26]. TensorFlow[27] and Scikit-learn[28] were also used for efficient management of deep learning models and for defining the model. The implementation of model makes use of GPU enable device for easier and faster processing.

4. Results and Discussion

We trained our proposed model using DenseNet-169 on a combination of dataset from Diabetic Retinopathy Detection 2015[21] and APTOS 2019 blindness detection[22] from kaggle. There was a lot of noise associated with the images provided by the dataset therefore, preprocessing was needed. For preprocessing, we first removed the black border of the images in order to focus more on the fundus image only, black corners of images was also removed, then the images were resized to a standard format of 256*256 of width and height. At last a Gaussian blur was applied to the images in order to remove the Gaussian noise. After preprocessing we analyze that the data is highly unbalanced among the severity classes, majority of data belonged to the class '0'.i.e. No DR. in order to address this issue, we used data augmentation, which gives us 7000 images from each severity class and made the data balanced. After preprocessing and augmentation of images, data was finally fed to the DenseNet-169 for training the model. After evaluating our model the training accuracy of 0.953 was obtained, while as validation accuracy of 0.9034 was achieved. We also calculated the Cohen Kappa score which comes out to be 0.804. We also applied a regression model to our dataset and compute its validation accuracy which is 0.789. Our proposed model outperforms the regression model. The results of our model are summarized in table 1.

Table 1 Result of the Proposed Model

Training Accuracy	Validation Accuracy	Cohen kappa score
95%	90%	80%

The figure 12 shows the comparison between the accuracies obtained by the proposed model and regression model.

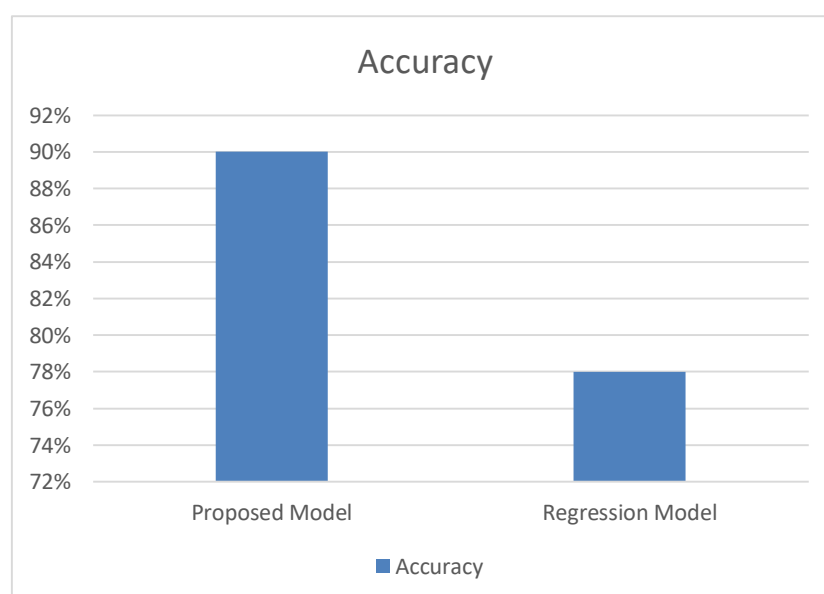


Figure 12 Accuracy Obtained By Proposed Model and Regression Model

Besides Regression model, the proposed model was compared to a number of machine learning classifiers like Support Vector Machine (SVM), K-Nearest Neighbor (KNN) and Decision Tree (DT). The results are summarized in the table 2, where accuracies of the different classifiers are given.

Table 2 Results Obtained By Various Classifiers

CLASSIFIER	DATASET	ACCURACY	DR CLASSES
SVM[29]	Messidor, Diabeticret DB1.	85.6%	Normal, Non PDR, PDR.
DT[30]	Messidor	85.1%	Normal, Mild, Moderate, Severe.
KNN[29]	Messidor, Diabeticret DB1	55.1%	Normal, Non PDR, PDR.
Regression	Diabetic Retinopathy Detection 2015 &APTOS 2019 from kaggle.	78%	No DR, Mild, Moderate, Severe and Proliferative DR.
Proposed Model	Diabetic Retinopathy Detection 2015 &APTOS 2019 from kaggle.	90%	No DR, Mild, Moderate, Severe and Proliferative DR.

The proposed model achieves the highest accuracy of 90%, followed by SVM with an accuracy of 85.6%, Decision Tree with 85.1%, Regression with 78%, and KNN with the least accuracy of 55.17%.

Figure 13 shows comparison between the classifiers in which the proposed model shows the highest accuracy among other classifiers.

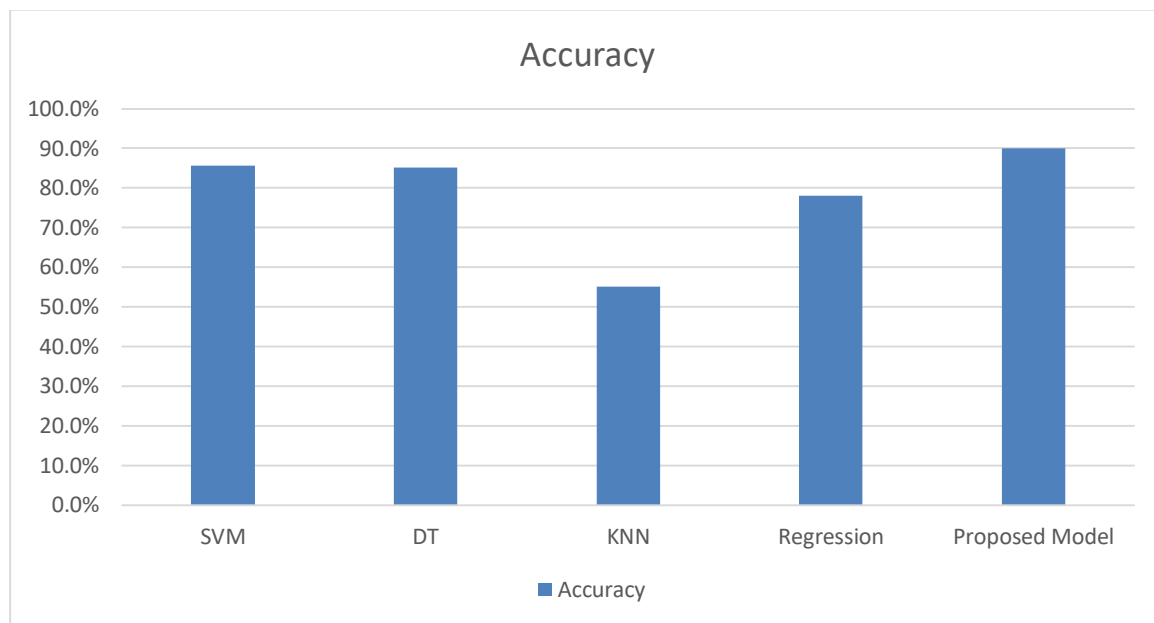


Figure 13 Accuracy Obtained By Various Classifiers.

5. Conclusion

Traditional method for detection of DR is prolonged, challenging and costly, thus many researches were brought up to automate the detection process by using machine learning and deep learning approaches. In this work, we presented a comprehensive study of various methodologies for detecting diabetic retinopathy automatically and attempted to propose our own deep learning approach for the early diagnosis of retinopathy by using a DenseNet-169(which is a new CNN architecture, having many deep layers). Two datasets: ‘Diabetic Retinopathy Detection 2015’and ‘APTOS 2019 blindness detection’ from kaggle were used together for this study. A lot of preprocessing and augmentation was done to standardize the data in a desired format and to remove the unwanted noise. Beside DenseNet-169 classifier, we also used a regression model to draw the comparison between the results. Moreover, machine learning classifiers like SVM, DT and KNN were compared with the proposed system. Where the best accuracy among all was obtained by the proposed model and it also classifies the images into more no of classes. Our proposed model performed better than the regression model by achieving the accuracy of 90% however, 78% accuracy was yielded by the regression model.

6. Limitation and Future Scope

As there are a number of images taken under different conditions, needs to undergo a lot of preprocessing and augmentation, some features of image might be missed out, so such techniques should be used that not only preserve all the tiny important features but at the same time is able to do a successful pre-processing. Moreover multiple images should be provided for every patient which would in turn increase the possibility of classifying the images correctly as more information can be gathered rather than only two images per person. The possibility of tweaking hyper-parameters is constantly growing with the emergence of new neural networks through better pooling methods. Such methods can be considered for future work to uncover the possibilities of increasing performance in this area. Furthermore, using different networks for training the model by the process of ensemble can also lead towards the better

results. As different model have their own advantages in terms of performance, if tied together, can help in improving overall productivity of a system rather than an individual model. We have used two datasets in our study, using more no of datasets or a combination of various datasets may improve the generalizability. The deployment of such systems can be done by using the MobileNet, which is a convolutional neural network for developing mobile applications. The web applications can be developed that can work for windows, Linux and Android operating systems as a diabetic retinopathy diagnostic tool.

References

- [1] <https://www.medicalnewstoday.com/articles/323627>.
- [2] <https://www.mayoclinic.org/diseases-conditions/diabetic-retinopathy/symptoms-causes/syc-20371611>.
- [3] S. K. Pandey and V. Sharma, "World diabetes day 2018: Battling the Emerging Epidemic of Diabetic Retinopathy," *Indian J Ophthalmol*.
- [4] https://www.health.harvard.edu/a_to_z/retinopathy-a-to-z
- [5] <https://missinglink.ai/guides/convolutional-neural-networks/convolutional-neural-networks-architecture-forging-pathways-future/>
- [6] J. De Calleja, L. Tecuapetla, and M. A. Medina, "LBP and Machine Learning for Diabetic Retinopathy Detection," pp. 110–117, 2014.
- [7] U. R. Acharya, C. M. Lim, E. Y. K. Ng, C. Chee, and T. Tamura, "Computer-based detection of diabetes retinopathy stages using digital fundus images," *Proc. Inst. Mech. Eng. Part H J. Eng. Med.*, vol. 223, no. 5, pp. 545–553, 2009, doi: 10.1243/09544119JEIM486.
- [8] K. A. Anant, T. Ghorpade, and V. Jethani, "Diabetic retinopathy detection through image mining for type 2 diabetes," in *2017 International Conference on Computer Communication and Informatics, ICCCI 2017*, 2017, doi: 10.1109/ICCCI.2017.8117738.
- [9] M. Gandhi and R. Dhanasekaran, "Diagnosis of diabetic retinopathy using morphological process and SVM classifier," *Int. Conf. Commun. Signal Process. ICCSP 2013 - Proc.*, pp. 873–877, 2013, doi: 10.1109/iccsp.2013.6577181.
- [10] J. I. Orlando, E. Prokofyeva, M. del Fresno, and M. B. Blaschko, "An ensemble deep learning based approach for red lesion detection in fundus images," *Comput. Methods Programs Biomed.*, vol. 153, pp. 115–127, 2018, doi: 10.1016/j.cmpb.2017.10.017.
- [11] S. Preetha, N. Chandan, K. Darshan N, and B. Gowrav P, "Diabetes Disease Prediction Using Machine Learning," *Int. J. Recent trends Eng. Res.*, vol. 6, no. 5, 2020, doi: 10.23883/IJRTER.2020.6029.65Q5H.
- [12] S. R. Sadda *et al.*, "Quantitative assessment of the severity of diabetic retinopathy," *Am. J. Ophthalmol.*, 2020, doi: 10.1016/j.ajo.2020.05.021.
- [13] J. Amin, M. Sharif, and M. Yasmin, "A Review on Recent Developments for Detection of Diabetic Retinopathy," *Scientifica*, vol. 2016. 2016, doi: 10.1155/2016/6838976.
- [14] Y. Kumaran and C. M. Patil, "A brief review of the detection of diabetic retinopathy in human eyes using pre-processing & segmentation techniques," *International Journal of Recent Technology and Engineering*, vol. 7, no. 4. pp. 310–320, 2018.
- [15] M. Chetoui, M. A. Akhloufi, and M. Kardouchi, "Diabetic Retinopathy Detection Using Machine Learning and Texture Features," in *Canadian Conference on Electrical and Computer Engineering*, 2018, vol. 2018-May, doi: 10.1109/CCECE.2018.8447809.
- [16] I. Sadek, M. Elawady, and A. E. R. Shabayek, "Automatic Classification of Bright Retinal Lesions via Deep Network Features," pp. 1–20, 2017.

- [17] G. T. Zago, R. V. Andreão, B. Dorizzi, and E. O. Teatini Salles, “Diabetic retinopathy detection using red lesion localization and convolutional neural networks,” *Comput. Biol. Med.*, vol. 116, p. 103537, 2020, doi: 10.1016/j.compbiomed.2019.103537.
- [18] D. Doshi, A. Shenoy, D. Sidhpura, and P. Gharpure, “Diabetic retinopathy detection using deep convolutional neural networks,” in *International Conference on Computing, Analytics and Security Trends, CAST 2016*, 2017, pp. 261–266, doi: 10.1109/CAST.2016.7914977.
- [19] P. Kaur, S. Chatterjee, and D. Singh, “Neural network technique for diabetic retinopathy detection,” *Int. J. Eng. Adv. Technol.*, vol. 8, no. 6, pp. 440–445, 2019, doi: 10.35940/ijeat.E7835.088619.
- [20] M. Voets, K. Møllersen, and L. A. Bongo, “Reproduction study using public data of: Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs,” *PLoS One*, vol. 14, no. 6, pp. 1–11, 2019, doi: 10.1371/journal.pone.0217541.
- [21] “Diabetic Retinopathy Detection Identify signs of diabetic retinopathy in eye images,” 2015. [Online]. Available: <https://www.kaggle.com/c/diabetic-retinopathy-detection/data>.
- [22] “APTOS 2019 Blindness Detection Detect diabetic retinopathy to stop blindness before it’s too late,” 2019. [Online]. Available: <https://www.kaggle.com/c/aptos2019-blindness-detection/data>.
- [23] <https://towardsdatascience.com/the-most-intuitive-and-easiest-guide-for-convolutional-neural-network-3607be47480>.
- [24] <https://www.kaggle.com/pytorch/densenet169>.
- [25] OpenCV Library opencv.org.
- [26] <http://www.numpy.org/>.
- [27] <https://www.tensorflow.org/>.
- [28] <https://scikit-learn.org/>.
- [29] S. Gupta, “Diagnosis of Diabetic Retinopathy using Machine Learning,” vol. 3, no. 2, 2015, doi: 10.4172/2311-3278.
- [30] E. V Carrera and R. Carrera, “Automated detection of diabetic retinopathy using SVM,” pp. 6–9, 2017.
- [31] “World Health Organization.” [Online]. Available: <https://www.who.int/news-room/fact-sheets/detail/diabetes>.