



AUTOMATED METHODS OF DIABETIC RETINOPATHY DETECTION: FROM TRADITIONAL TO DEEP LEARNING STRATEGIES - A REVIEW

Laxmikant S. Kalkonde Research Scholar of Department of Electronics and Telecommunication Engineering PRMCEAM, Badnera-Amravati, M.S. (India)

Dr.K.N.Kasat Assistant Professor of Department of Electronics and Telecommunication Engineering PRMCEAM, Badnera-Amravati, M.S. (India)

Kaustubh S. Kalkonde, Dinesh S. Chandak, Department of Electrical Engineering, PRMCEAM, Badnera Amravati, M.S.(India). laxmikant.kalkonde@prmceam.ac.in

Abstract: Diabetic Retinopathy (DR) is a common eye issue that results in an infected eye moreover it leads to vision loss. Because disease generally impacts people in their productive years of life, diabetic retinopathy has a significant effect on both the patient and society. It is necessary to offer a reliable remedy and a means of locating the illness on the field, to accurately diagnose the population's overall diabetes-related retinopathy. However, there is a need for automatic approaches to streamline the recognition process of diabetic retinopathy. Wherein, retinal fundus images are considered the significant modality. These images are used to extract blood vessels, microaneurysms, and exudates, which provide valuable features for diabetic retinopathy detection. These features provide creditable inputs to define the feature vector. Further, utilizing it as input for the detection model. This paper focuses on the evolution of methods in diabetic retinopathy detection, traversing from traditional techniques to modern innovations, including the application of deep learning strategies. We will evaluate these methods by examining their techniques and addressing research challenges. The effectiveness of the detection methods will be manifested by analyzing the methods based on the benchmarking parameters, such as sensitivity, specificity, accuracy and ROC curve.

Keywords: Benchmarking parameters, Blood vessels, Deep learning strategies, Detection Methods, Diabetic Retinopathy, Feature vector, Vision loss

Introduction: Diabetes is a serious issue that people are facing worldwide specially it is due to elevated levels of blood sugar, which leads deliberate damage to the heart, blood vessels, eyes, kidneys and nerves. World Health Organization (WHO) estimates that approximately 422 million people found positive for diabetes. To validate this data figure 1 indicates prevalence of diabetes in few Asian countries Pakistan being heights and Australia's percentage recorded at lower side (Wise Voter 2023). DR is one of the most frequent diseases that emerge in a human eye, resulting into loss of eyesight if not diagnosed and treated at its early phase. Generally, DR is noticed in people who suffer from diabetes disease, and these people have the possibility of losing their vision of about 20% as compared to healthy people. According to medical practitioner, risk of DR is related with the duration of uncontrolled sugar level. For instance 10 years of diabetes have a notable prevalence of DR, and this risk increase to about 63% particularly diabetes persist for 15 years or more. The possibility of causing DR may DR is originated due to the deterioration of blood vessels that are responsible for nurturing the retina. In the primary phase, DR progress silently with no symptoms or may develop only slight problems in vision, and in the final stage, it leads to blindness.

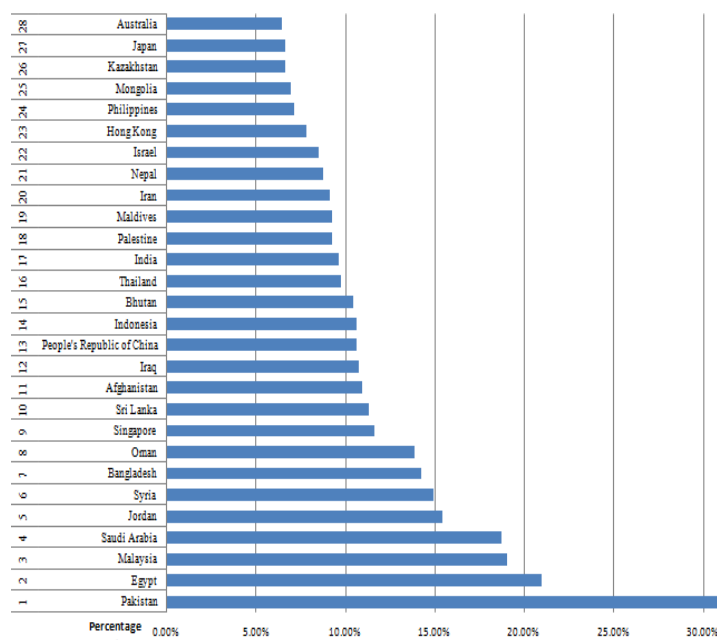
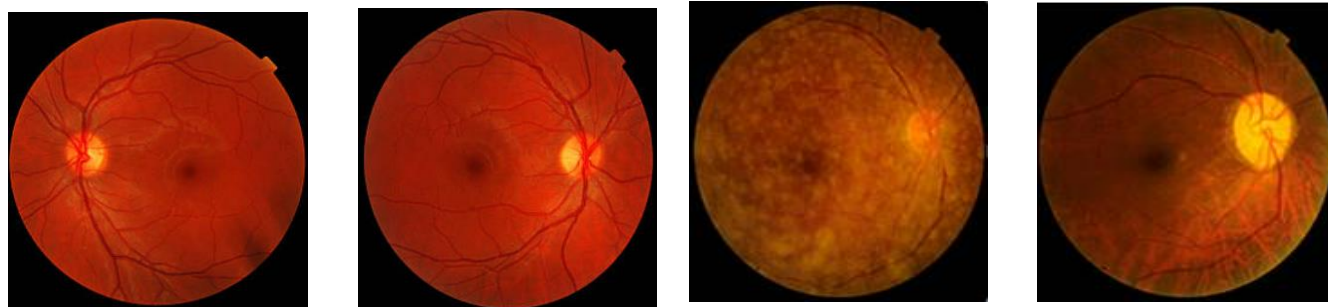


Fig 1: Prevalence of Diabetes in few Asian Countries

Figure 2 illustrates a comparison between a healthy retina and one that has been modified due to inadequate control of glucose levels.



2(a)

2 (b)

Fig 2: Image of Retina a. Healthy b. DR

This paper is framed in the below mentioned order. Starting with “Introduction” it provides basic information on diabetes, WHO data and DR is briefly discussed. Review of existing literature is provided in “Related Work”. Section 2 focuses on methodologies; it covers both traditional and deep learning approaches, as well as providing insights into the datasets related to Diabetic Retinopathy (DR). Section 3 summaries objectives of paper. Next section is of “Benchmarking Parameters” which elaborates essential parameters with comparative bar graph of obtained results by researches. Section VI summarizes the paper findings and future scope for DR research enhancement.

1. Related Work:

The desertion of blood vessels influences the growth of vascular wall, which result in extravasations of substances, such as blood plasma, and at the last stage, the blood may emerge (Morales et al., 2017). The successful identification to heal the eye disease is the detection of it early as possible through the periodic screening of the fundus. Number of searchers has been introduced to build DR detection strategies using different intelligent computing methodologies to attain enhanced recognition performance. The treatment for DR can be provided by the laser or a surgical process termed as vitrectomy, which avoids vascular variations and saves vision (Kadan & Subbian, 2021). To assure accurate diagnosis, angiography is conducted, in which a dye is interleaved in the arm that

passes to the blood vessels of the retina and gets illuminated. This involves in detection of the changes in the blood vessel and also leakages of blood in the retina. It is necessary to note that blood sugar of higher levels damages the blood vessels of the retina, which boost the probability of fluid bleeding and leakage (Gadekallu et al., 2020). To notice the diseases in the eye in well-structured mode, image processing came into depiction. The accurate discovery executed by the image processing strategy help to monitor, and diagnose the patient's eye (Klein et al., 2009). The composition of the blood vessels at the retina indicates the data corresponding to the variations that occur in the structure of the eye (Teng et al., 2002). Some of the characteristics of the eye, such as Optic Disc (OD) and vascular blood vessels can be used for the recognition of DR in addition to the other diseases related to the eye. A number of monitoring instruments are available to sense DR. Furthermore, the images of the retinal vessel are captured using the Digital fundus cameras. Hence, the procedure of attaining fundus images shows up the image quality in some portions, which looks for better image improvement strategies (Saha et al., 2019). Normal and anomalous classes are discriminated by means of the preprocess images or object patches by utilizing supervised learning approach. The manual explanation of DR lesions for DR evaluation of retinal images is costly. As a consequence; it obstructs the arrangement of vast training datasets, through which the data-driven strategies may enhance to accept several DR states (Pires et al., 2019). Traditional DR detection methods comprise of improving image quality, Segmentation, Feature Extraction, and Categorization steps. The main objective of paradigm shift from conventional to the artificial intelligence-based machine learning models is not only to reduce the efforts with huge database size but also operating cost, which results in enhanced response from designed system. It has been observed that, the future difficulties and improbability is encountered while using the conventional methods because of manual extraction of features. Under these states, deep learning methods are considered, which has stimulated the attention of researchers in the present era, as it embraces the advantageous capability to obtain the idea related to the significant features directly from the fundus images (Kadan & Subbian, 2021). A human being is much productive in the middle age of life but slow killer diseases impacts; diabetic retinopathy has a significant effect on both the patient and society. It is necessary to offer a reliable remedy and a means of locating the illness on the field, to accurately diagnose the population's overall diabetes-related retinopathy. The researchers are working on an improved detection model approach for the investigation of DR using high class retinal images and accuracy classifying its severity. This approach can identify the complex feature to decrease computational efficiency and give the method greater convergence. Research gaps in existing literature are address below:

- i. The Random Forest (RF) approach was introduced by (Saleh et al., 2018) which suggested increased sensitivity and specificity, but there exist more number of matching rules (Nair & Muthuvel, 2020). Also, the RF strategy was used by (Gupta et al., 2017), which required evaluation of huge systems for the grading of DR (Nair & Muthuvel, 2020).
- ii. Fundus photography was developed by (Gräsbeck et al., 2016), which provided better accuracy and also provided enhanced photographic outcomes, however acts as an exacting strategy when illustrious with clinical setting needs (Nair & Muthuvel, 2020).
- iii. A Computer Aided Diagnostic system (CAD) was used in (Gegundez-Arias et al., 2017) that performed as an efficient method with the provision of increased measure of sensitivity and specificity, there exists a possibility for the occurrence of false negatives in mild states (Nair & Muthuvel, 2020).

RF strategy implemented by (Tavakoli et al., 2013) minimized the burden of manual work, but the increase in step size raises the computational trouble (Nair & Muthuvel, 2020). Limitations in existing knowledge in the blood vessel-based diabetic retinopathy techniques are summarized in below table:

Table 1 Analyzed articles and identified research challenges

Sr. No.	Author	Method used	Research Challenges
1	Gundluru et al., (2022)	optimization algorithm with deep learning model is implemented	Higher level of overfitting issues.
2	Yaqoob et al., (2021)	Deep features are extracted with ResNet and adopted classification technique is random forest	Increase the error rate.
3	Kadan & Subbian, (2021)	Iterative blood vessel segmentation process and optimized hybrid classifier and.	Exhibit poor performance in case of less amount of data
4	Math & Fatima, (2021)	Adaptive ML classification	Availability of only limited power for computation
5	Das et al., (2021)	DL architecture based on segmented fundus image	Large data is needed for training
6	Gayathri et al., (2020)	A lightweight CNN approach with various classifiers	generalization and scalability for other retinal diseases
7	Samanta et al., (2020)	CNN Convolutional neural networks on a small dataset	The model is not capable to classify Mild phase of DR
8	Gayathri et al., (2020)	Use of ADTCWT for classification using haralick and multiresolution features	May result in loss of textures with the use of Haralick features
9	Gadekallu et al., (2020)	DNNs to predict DR	Not suitable for larger datasets of higher dimensions
10	Shankar et al., (2020)	Hyper parameter tuning deep learning	Inception-v4 is time-consuming, due to the existence of extensive layers
11	Nair & Muthuvel, (2020)	Blood vessel segmentation and MCS-NS algorithm	reduced precision and low convergence rate
12	Luo et al., (2023)	A DNNs with mining local and long-range dependence	The error rate is maximum
13	Kobat et al., (2022)	detection using horizontal and vertical patch division-based pre-trained Dense NET	High power consumption
14	Sungheetha & Sharma (2021)	deep feature extraction-based convolution neural network	Large computational power and memory usage
15	Ming et al. (2021)	artificial intelligence-based screening system	A Large amount of is time needed for the small sample size.
16	Luo et al., (2021)	Multi-view DCNNs and integrated attention mechanisms	Multi view detection was not support for the lesion annotations.
17	Ashir et al. (2021)	local extrema information and quantized haralick features	The method required much more robust approaches.
18	Hacisoftaoglu et al., (2020)	Deep learning frameworks with smart phone-based retinal imaging systems	Higher battery capacity and computational power.
19	Bibi et al., (2020)	Automated detection of DR using fused features	It has less robust power during the real time performance.
20	Wang et al., (2020)	Deep learning artificial intelligence	The quality of the image is poor which increase the error rate.

21	Qiao et al., (2020)	non-proliferative DR detection using deep learning algorithms	takes high time for computation
22	Zago et al., (2020)	localization and convolutional neural networks.	does not give the labels of hemorrhage, which acts as the significant indicators of DR
23	Park et al., (2020)	Adopted Segmentation M-GAN: with DFCNs	Slower process, imputing the computation time.

2. Methodology and Dataset: In the following subsections, the generalized methodologies used for traditional and deep learning approaches are discussed. Additionally, imaging techniques for patient care and available datasets are explored.

2.1 Methodology: The main pathology indications in retinal images are abnormal blood vessels, microaneurysms, hemorrhage and hard exudate. This signs helps researcher to detect type of DR. Figure 3 illustrates the primary steps involved in traditional method

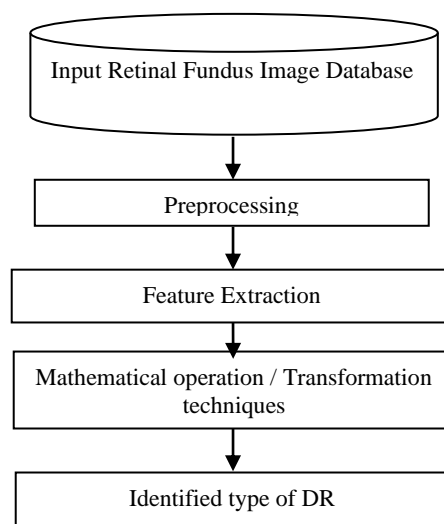


Fig 3: Traditional Method

In the traditional method, researchers have identified the type of Diabetic Retinopathy (DR) using the above steps, referred to as the training phase of the model. However, during the testing phase, the same steps are repeated for a query image, followed by a distance calculation technique with available images in the trained database.

In recent times, researchers have shifted their focus towards deep learning strategies. This paradigm shift is primarily motivated by the presence of diverse, unstructured, inter-connected, and large-scale medical image datasets. Figure 4 illustrates the basic steps involved in the deep learning approach.

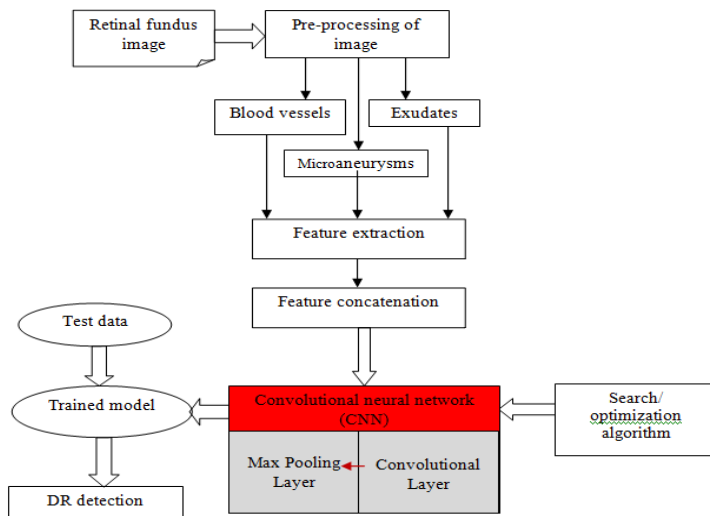


Fig 4: Deep learning approach

In this process, a retinal fundus image serves as the input and undergoes a preprocessing step, followed by the extraction of features from the pathology indicators of Diabetic Retinopathy (DR). The extracted features are then concatenated and used as input for a Convolutional Neural Network (CNN) classifier, as outlined by (Ramachandran et al., 2018). Here, CNN includes convolutional and max-pooling layers, with the flexibility to repeat these operations as needed.

The weights of the CNN are fine-tuned optimally using an optimization algorithm. During the testing phase, when new data is provided to the trained model, the incoming data undergoes the feature extraction process. Subsequently, the proposed model is applied to test the data, aiming to detect the presence of Diabetic Retinopathy (DR).

2.2. Dataset: A patient-centered approach in selecting retinal imaging modalities is essential for providing personalized and effective care. Table 2 illustrates various imaging techniques and their unique key benefits of the retina and ocular structures.

Table 2 Imaging techniques

Method	Key Benefits
Color Fundus Photography	A detailed color representation of the back of the eye
Fluorescein Angiography (FA)	Highlights blood vessels
Indocyanine Green Angiography (ICGA)	Similar to FA (different dye approach)
Optical Coherence Tomography (OCT)	High resolution and detailed structural analysis
B-scan Ultrasonography	Using sound waves posterior segment of eye is studied
Fundus Auto fluorescence (FAF)	Provides natural fluorescence of retinal structures

The choice of imaging techniques depends on subject under treatment.

Till today research is carried out on DR diagnosis using available datasets, the images captured are taken from fundus camera. Several datasets, such as *IDRiD*, *DRD* and *MESSIDOR* have played a vital role in leveraging the research in this domain. The brief information about mentioned datasets is provided below:

2.2.1 Indian Diabetic Retinopathy Image Dataset (IDRiD): It is an open access dataset. The dataset is structured into three main components: Segmentation, Disease Grading, and Localization, each addressing specific aspects of diabetic retinopathy analysis (Prasanna Porwal et al. in 2018).

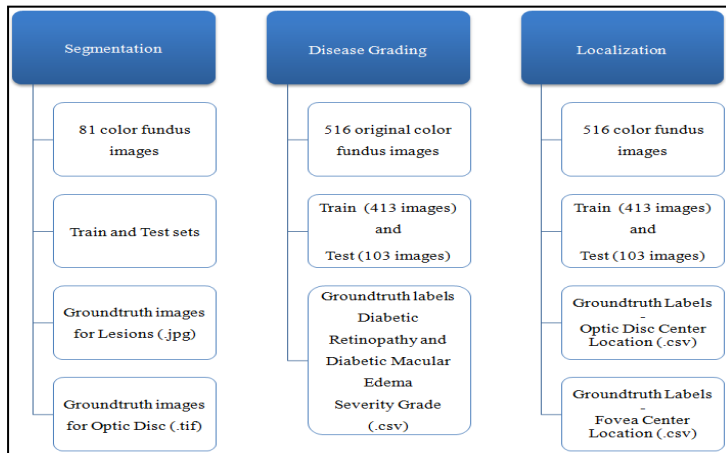


Fig 5: A Comprehensive dataset - *IDRiD*

2.2.2 Kaggle Diabetic Retinopathy Detection Training Dataset (DRD): It contains 32,156 high-resolution retinal images annotated by ophthalmologist with assigned diabetic retinopathy score on a scale of 0 to 4. Table 3 illustrates details of dataset (DRD 2019).

Table 3 DRD details

Scale	DR Type	Number of Images
0	No DR	25810
1	Mild	2443
2	Modrate	5292
3	Severe	873
4	Proliferative DR	708

2.2. 3 MESSIDOR: It stands for Methods to Evaluate Segmentation and Indexing Techniques in the field of Retinal Ophthalmology. Here, 1200 retinal fundus images are presented in TIFF format, with medical expert comments for each image. However, expert recommendation provides valuable insights into the research (Messidor- ADCIS, 2020).

3. Objectives: This paper is aimed to reflect performance of traditional methods approaches so as to identify their research challenges. Further, to understand how innovative technologies, such as machine and deep learning, can improve early detection and management of DR same will be beneficial to healthcare sector and patient.

4. Benchmarking Parameters: To analyze the performance of detection methods the required parameters are sensitivity, specificity, accuracy and ROC curve. Moreover, they serve to assist model's evaluation capacity in referring normal and anomalies. Medical professionals use these measures to determine the reliability and utility of a diagnostic test in clinical practice.

4.1 TPR or Sensitivity: In the context of predictive behavior of diagnostic test, TP outcomes into genuine identification of disease if present among all individuals is termed as True positive rate or sensitivity and it is given by

$$Sensitivity = \frac{TP}{TP + FN} \quad (1)$$

The parameter also called as Recall.

4.2 Specificity: The parameter outcomes into indisputable identification of true negative results among all individuals who are actually disease-free. Specificity indicates how well a test can exclude individuals without the condition.

$$Specificity = \frac{TN}{TN + FP} \quad (2)$$

Above two parameters are summarized in below table -

Table 4 Summary

Parameter	Obtained value	Remark
Sensitivity	High	Low rate of FN (rarely misses the disease)
Specificity	High	Low rate of FP (rarely misidentifies healthy individuals as having the disease)

4.3 Accuracy: Accuracy is a measure of how well a diagnostic test correctly identifies both healthy and anomaly cases. Here, sensitivity and specificity are combined together to comment test's performance. However, it is to be noted that the accuracy can be influenced by the prevalence of the disease in the tested population. In situations where the disease is rare, accuracy may not be the most informative metric.

$$Accuracy = \frac{(TP + TN)}{TP + FN + TN + FP} \quad (3)$$

Where,

TP – True Positive; TN – True Negative FN – False Negative; FP – False Positive

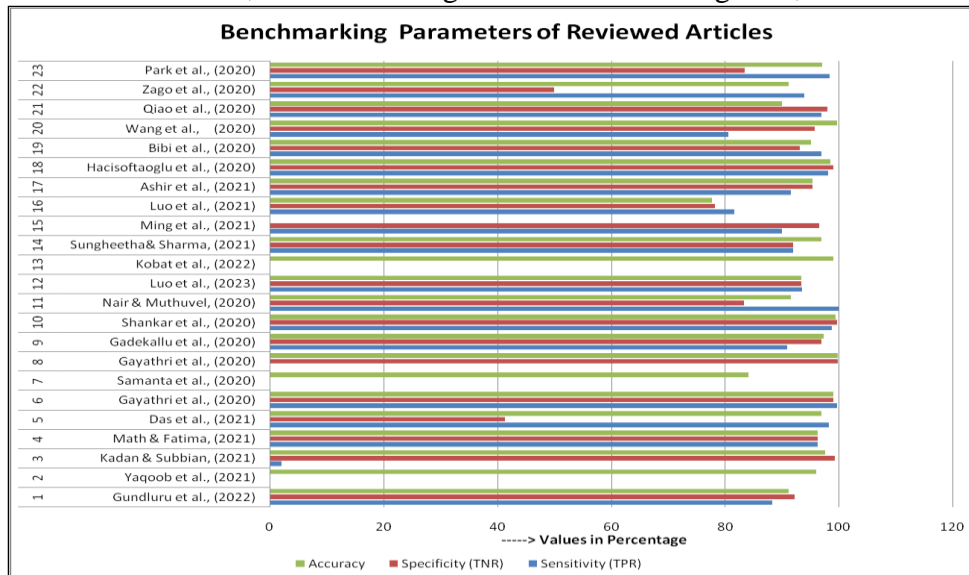


Fig 6: Benchmarking: sensitivity, specificity and accuracy

Above figure depicts benchmarking of three parameters namely sensitivity, specificity and accuracy. Each individual author has contributed towards enchanting the performance of the incorporated method, but explicitly contributions by (Gayatheri et al., 2020), (Shankar et al., 2020) and (Wang et al., 2020) is remarkable.

The assessment of sensitivity, specificity, and accuracy is dominant in research studies as these metrics collectively provide a comprehensive evaluation of a method's performance, enabling understanding of its ability to correctly identify true positives, true negatives, and overall predictive effectiveness.

4.4 ROC: Receiver operating characteristic curve is plotted w.r.t. TPR or sensitivity and FPR. Equation 4 represents FPR formula.

$$FPR = \frac{FP}{FP + TN} \quad (4)$$

Where, FPR – False positive rate

ROC shows model's ability to classify the healthy and anomalous instances. Standard ROC curve is show in figure 7 with its interpretation.

The classifier performance will be decided based on the curve (here red dotted curve) is lying above the reference line, indicating that the classifier performs better than random chance. It is to be advised that the actual shape of curve may vary according to performance of designed model and the

assumed threshold values.

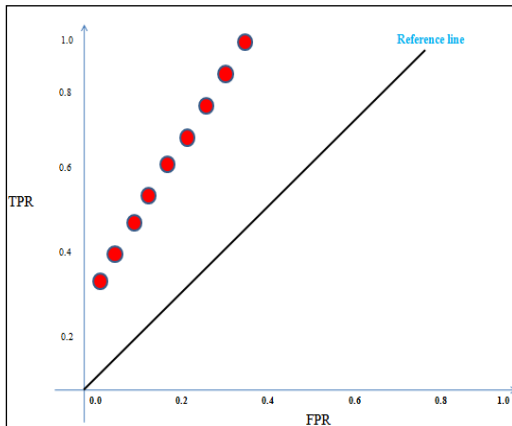


Fig 7: ROC curve

Apart from above mentioned parameters it has been observed that in multiclass classification, where much needed thing is to maintain tradeoff in between human annotations and model prediction. A parameter termed as Cohen's Kappa would be helpful (Samanta et al., 2020).

These parameters help researchers to quantitatively assess the performance of their models or algorithms, and they play a vital role in comparing different approaches in the literature. Better Understanding and reporting these metrics enhance the transparency and reproducibility of research findings.

5. Conclusion

In this paper, we have seen the insights of various traditional techniques. Wherein, these techniques had laid a path for primary diagnostic framework. But encountered difficulty is not only of obtained results but also of limitations in database size. However, researchers have shown interest to leverage this challenging situation with cutting-edge techniques such as NN, CNNs- convolutional neural networks, machine and deep learning. Through our analysis we can conclude that biomedical field will experience paradigm shift in terms of aforementioned parameters of section IV. Still scope of improvement is much needed in terms of incremental learning, segmentation method and statistical analysis on blood vessels. Furthermore, all existing methods for diabetic retinopathy (DR) diagnosis rely on available retinal fundus images. Surprisingly, no research has explored alternative image databases concerning various imaging techniques.

References

- [1] Ashir, A. M., et al. "Diabetic retinopathy detection using local extrema quantized haralick features with long short-term memory network." *International Journal of Biomedical Imaging* (2021).
- [2] Bibi, I., Mir, J., and Raja, G. "Automated detection of diabetic retinopathy in fundus images using fused features." *Physical and Engineering Sciences in Medicine* 43, no. 4 (2020): 1253-1264.
- [3] Das, S., et al. "Deep learning architecture based on segmented fundus image features for classification of diabetic retinopathy." *Biomedical Signal Processing and Control* 68 (2021): 102600.
- [4] Gadekallu, T. R., et al. "Deep neural networks to predict diabetic retinopathy." *Journal of Ambient Intelligence and Humanized Computing* (2020): 1-14.
- [5] Gayathri, S., Gopi, V. P., and Palanisamy, P. "A lightweight CNN for Diabetic Retinopathy classification from fundus images." *Biomedical Signal Processing and Control* 62 (2020): 102115.
- [6] Gayathri, S., et al. "Automated binary and multiclass classification of diabetic retinopathy using haralick and multiresolution features." *IEEE Access* 8 (2020): 57497-57504.
- [7] Gegundez-Arias, M. E., et al. "A tool for automated diabetic retinopathy pre-screening based on retinal image computer analysis." *Computers in Biology and Medicine* 88 (2017): 100-109.

- [8] Gräsbeck, T. C., et al. "Fundus photography as a screening method for diabetic retinopathy in children with type 1 diabetes: outcome of the initial photography." *American Journal of Ophthalmology* 169 (2016): 227-234.
- [9] Gundluru, N., et al. "Enhancement of detection of diabetic retinopathy using Harris hawks optimization with deep learning model." *Computational Intelligence and Neuroscience* (2022).
- [10] Gupta, G., et al. "Local characterization of neovascularization and identification of proliferative diabetic retinopathy in retinal fundus images." *Computerized Medical Imaging and Graphics* 55 (2017): 124-132.
- [11] Hacısoftaoglu, R. E., et al. "Deep learning frameworks for diabetic retinopathy detection with smartphone-based retinal imaging systems." *Pattern Recognition Letters* 135 (2020): 409-417.
- [12] Kadan, A. B., and Subbian, P. S. "Optimized hybrid classifier for diagnosing diabetic retinopathy: iterative blood vessel segmentation process." *International Journal of Imaging Systems and Technology* 31, no. 2 (2021): 1009-1033.
- [13] Klein, R., et al. "The Wisconsin Epidemiologic Study of Diabetic Retinopathy XXIII: the twenty-five-year incidence of macular edema in persons with type 1 diabetes." *Ophthalmology* 116, no. 3 (2009): 497-503.
- [14] Kobat, S. G., et al. "Automated diabetic retinopathy detection using horizontal and vertical patch division-based pre-trained DenseNET with digital fundus images." *Diagnostics* 12, no. 8 (2022): 1975.
- [15] Luo, X., et al. "MVDRNet: Multi-view diabetic retinopathy detection by combining DCNNs and attention mechanisms." *Pattern Recognition* 120 (2021): 108104.
- [16] Luo, X., et al. "A deep convolutional neural network for diabetic retinopathy detection via mining local and long-range dependence." *CAAI Transactions on Intelligence Technology* (2023).
- [17] Math, L., and Fatima, R. "Adaptive machine learning classification for diabetic retinopathy." *Multimedia Tools and Applications* 80, no. 4 (2021): 5173-5186.
- [18] Ming, S., et al. "Evaluation of a novel artificial intelligence-based screening system for diabetic retinopathy in the community of China: a real-world study." *International Ophthalmology* 41 (2021): 1291-1299.
- [19] Morales, Y., et al. "Digital tool for detecting diabetic retinopathy in retinography image using Gabor transform." *Journal of Physics: Conference Series* 792, no. 1 (2017): 012083.
- [20] Nair, A. T., and Muthuvel, K. "Blood vessel segmentation and diabetic retinopathy recognition: an intelligent approach." *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization* 8, no. 2 (2020): 169-181.
- [21] Park, K. B., Choi, S. H., and Lee, J. Y. "M-GAN: Retinal blood vessel segmentation by balancing losses through stacked deep fully convolutional networks." *IEEE Access* 8 (2020): 146308-146322.
- [22] Pires, R., et al. "A data-driven approach to referable diabetic retinopathy detection." *Artificial Intelligence in Medicine* 96 (2019): 93-106.
- [23] Qiao, L., Zhu, Y., and Zhou, H. "Diabetic retinopathy detection using prognosis of microaneurysms and early diagnosis system for non-proliferative diabetic retinopathy based on deep learning algorithms." *IEEE Access* 8 (2020): 104292-104302.
- [24] Ramachandran, N., et al. "Diabetic retinopathy screening using deep neural network." *Clinical & Experimental Ophthalmology* 46, no. 4 (2018): 412-416.
- [25] Saha, S. K., et al. "Color fundus image registration techniques and applications for automated analysis of diabetic retinopathy progression: A review." *Biomedical Signal Processing and Control* 47 (2019): 288-302.
- [26] Saleh, E., et al. "Learning ensemble classifiers for diabetic retinopathy assessment." *Artificial Intelligence in Medicine* 85 (2018): 50-63.
- [27] Samanta, A., et al. "Automated detection of diabetic retinopathy using convolutional neural networks on a small dataset." *Pattern Recognition Letters* 135 (2020): 293-298.

- [28] Shankar, K., et al. "Hyperparameter tuning deep learning for diabetic retinopathy fundus image classification." *IEEE Access* 8 (2020): 118164-118173.
- [29] Sungheetha, A., and Sharma, R. "Design an early detection and classification for diabetic retinopathy by deep feature extraction based convolution neural network." *Journal of Trends in Computer Science and Smart Technology (TCSST)* 3, no. 02 (2021): 81-94.
- [30] Tavakoli, M., et al. "A complementary method for automated detection of microaneurysms in fluorescein angiography fundus images to assess diabetic retinopathy." *Pattern Recognition* 46, no. 10 (2013): 2740-2753.
- [31] Teng, T., Lefley, M., and Claremont, D. "Progress towards automated diabetic ocular screening: a review of image analysis and intelligent systems for diabetic retinopathy." *Medical and Biological Engineering and Computing* 40 (2002): 2-13.
- [32] Wang, X. N., et al. "Automatic grading system for diabetic retinopathy diagnosis using deep learning artificial intelligence software." *Current Eye Research* 45, no. 12 (2020): 1550-1555.
- [33] Yaqoob, M. K., et al. "ResNet based deep features and random forest classifier for diabetic retinopathy detection." *Sensors* 21, no. 11 (2021): 3883.
- [34] Zago, G. T., et al. "Diabetic retinopathy detection using red lesion localization and convolutional neural networks." *Computers in Biology and Medicine* 116 (2020): 103537.
- [35] World Health Organization. "Diabetes." https://www.who.int/healthtopics/diabetes#tab=tab_1
- [36] "Wise Voter." WiseVoter. Accessed January 15, 2023. <https://wisevoter.com/country-rankings/diabetes-rates-by-country/>.
- [37] Porwal, Prasanna, et al. "Indian Diabetic Retinopathy Image Dataset (IDRiD)." *IEEE Dataport*. <https://dx.doi.org/10.21227/H25W98> (2018).
- [38] "Kaggle Diabetic Retinopathy Detection Training Dataset (DRD)." <https://academictorrents.com/details/08c244595c6cc4ec403b21023cf99c2b085cbc72>
- [39] "Messidor-ADCIS." http://www.adcis.net/en/third_party/messidor/ (accessed Jun.11, 2020).

AUTHORS

[1] **Laxmikant S. Kalkonde** is currently pursuing a Ph.D. in Electronics Engineering at SGBAU, Amravati University, India. With a substantial 14.4 years of professional experience. He is working as Assistant Professor in Department in Electronics & Telecommunication Engineering, PRMCEAM, Badnera. Also he worked as RF Engineer at Metro Wireless Engineering (India) Pvt. Ltd., Mumbai, he has managed turnkey projects like NSN-Bharti IBS, NSN-Maxis, and initiatives



for Reliance GSM. His interests span Machine Learning, Deep Learning, Digital Signal Processing, Image Processing, and Wireless Communication. He is an associate member of IETE and a Life Member of ISTE. He has made noteworthy contributions to the field with 12 research papers published in international/national journals and conferences. Additionally, SGBAU, Amravati University, has honored him with a color coat in the PPG category in "Aavishkar 2023".



[2] **Dr. K.N. Kasat** is presently working as Head of the Department in Electronics & Telecommunication Engineering, PRMCEAM, Badnera. She has 20 years of working experience. Her Areas of interest are power electronics, embedded systems. She is associate member of IETE and Life Member of ISTE. She has published 20 research papers in international journals and conferences.



[3] **Kaustubh S. Kalkonde** is currently enrolled in a doctoral program in Electronics Engineering at SGBAU, Amravati University, India. With an extensive 11 years of experience, his professional focus revolves around Digital Signal Processing, Image Processing, and Wireless Communication. He holds an associate membership with IETE and is a Life Member of ISTE. His contributions to the field include the publication of 7 research papers in esteemed international journals and conferences..



[4] **Dinesh Chandak** is currently pursuing a doctorate in Electronics Engineering at SGBAU, Amravati University, India. With 14 years of academic experience, his interests lie in Machine Learning, ANN, and Image Processing. He holds an associate membership with IEI and is a Life Member of ISTE. He has contributed significantly to the field with 10 research papers published in international/national journals and conferences, along with 1 Book Chapter.