Diabetic Retinopathy Classification using Various Machine Learning Techniques: A Review

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***Abstract*: Diabetes is common among those who have insulin issues. Only diabetics have diabetic retinopathy (DR), a devastating microvascular complication that destroys the retina and, if left misdiagnosed and untreated, can result in irreparable partial or whole blindness. In addition to the time it takes a patient to see an ophthalmologist who scans the patient's retina, many diabetics fail to recognize their illness and subsequently acquire visual impairments. Such human examination is time-consuming, slows the DR diagnosis method, allowing the illness to grow to more advanced stages within the window period, and is not always accurate. This article analyzes and evaluates the most recent research and survey articles addressing the precise diagnosis and classification of DR into distinct parts ranging from mild to severe.**

Keywords: Diabetic Retinopathy, Convolutional Neural Networks, Fundus images

I. INTRODUCTION

Diabetes is a condition in which the body cannot utilise insulin effectively or the gland does not secrete enough of it. According to WHO estimates, there are 442 million diabetics worldwide. This is a critical issue because India is the world's diabetes capital, with 77 million diabetics living there. Diabetes affects the retina's blood vessels gradually and accumulates over time, decreasing the patient's quality of life vision and culminating in diabetic retinopathy. When blood sugar levels rise abnormally, the excess blood sugar has no alternative but to gather in the blood vessels of the human eye. 10% of diabetic individuals who have had it for 10 to 15 years become blind, while 2% or so endure serious vision impairment. DR is the sixth most prevalent cause of partial blindness in adults of working age. Diabetic retinopathy progresses through several stages, including Diabetic retinopathy is characterized as mild, non-proliferative, proliferative, moderate, or severe in Fig. 1.

As a result of glucose buildup, the NPDR retina expands, causing blood vessel leaks in the eyes. As a result of the partial vascular blockage caused by severe edoema, the patient may lose portion of their vision. PDR, on the other hand, does not manifest until new blood vessels form in the retina. Because the fresh blood vessels were so sensitive, they were more prone to scar, limiting both central and peripheral vision and eventually causing total blindness. NPDR and PDR symptoms include blurred vision, fuzzy spots, haemorrhages, double vision, and micro vascular abnormalities. The blood from a haemorrhage causes partial or total vision loss. Furthermore, patients may experience floaters, black spots, and color perception issues. The most popular approach for diagnosing DR includes injecting a dye into the patient's arm vein and photographing the dye as it travels through the blood vessels in the eyes to look for blockages, leaks, and haemorrhages. The alternate method involves photographing the retina in cross-section, which aids in the detection of fluid leaks or retinal tissue damage. These traditional approaches are costly, time-consuming, and occasionally erroneous.

As a result, it is evident that early sickness detection is critical for saving patients' vision. The longer an illness goes undiscovered or untreated, the more serious the consequences may become. Machine learning (ML) technologies are used to forecast a wide range of diseases. CNN has successfully assisted in analysis and decision-making in computer vision, medicine design, medical image processing, and other domains. The use of cutting-edge machine learning algorithms has considerably decreased the stress of human interpretations by assisting in pathological screening and disease prediction. The use of CNN and ML in the identification of retinopathy was a natural and unavoidable issue with the sole objective of lowering the incidence. If diabetic retinopathy is given the awe-inspiring achievements of these technologies in a variety of other healthcare fields.

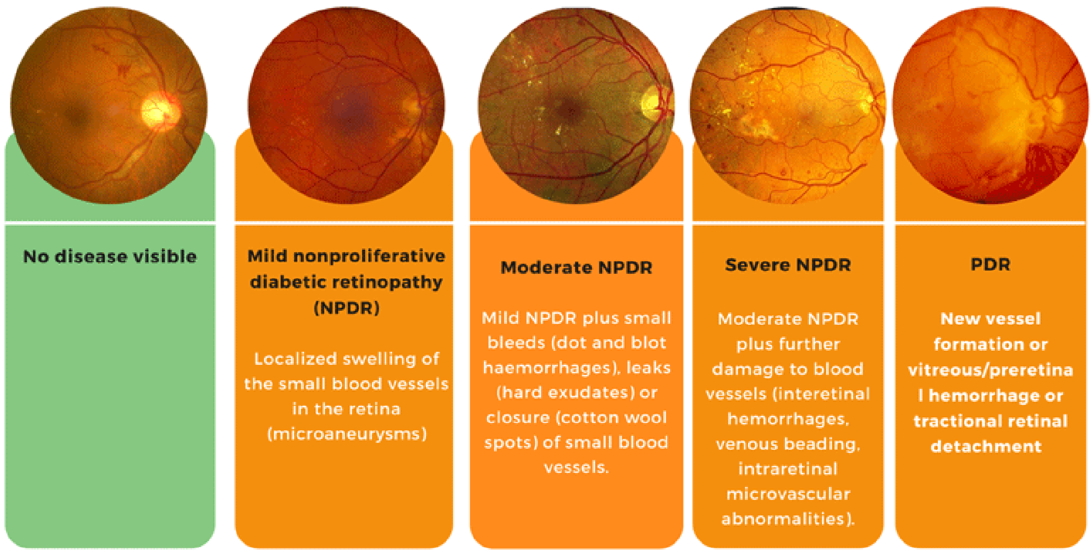

Fig 1: Five Classifications of Diabetic Retinopathy

II. LITERATURE SURVEY

Before the trial, AI system operators went through a standardized training process. Abramoff et al., in publication [1], produced the system the very first FDA-approved automated AI diagnosis gadget almost in any field of medicine may be able to help thousands of diabetics from losing their vision each year. The technique has been approved for use by healthcare practitioners to identify much milder DR and diabetic macular edema.

Surasak et al. built an application to recognize people in films in their study [2]. They created an application that consisted of three major components: human detection, human counting, and histogram generation. They recognized the human during the human identification procedure, presented the result with a green frame, and reported the number of people for each video frame. Using the HOG Algorithm, they studied every frame of the movie to detect and count persons. After analyzing the film from beginning to end, the application generates a histogram that displays the number of people observed over the length of the movie's running time.

The phases of DR are determined by the sorts of lesions that occur on the retina. In their study [3,] Wejdan et al. studied the most recent automated deep learning-based methods for diagnosing and categorizing diabetic retinopathy. We discussed the publicly accessible common funds DR datasets and provided a high-level overview of deep learning methodologies. CNN has been acknowledged by the majority of research for the detection and categorization of DR pictures because to its efficacy. The analysis also highlighted feasible ways for identifying and categorizing DR using DL.

Alyoubi et al. proposed two deep learning-based models, YOLOv3 and CNN512, in their work [4]. CNN512 and YOLOv3 were combined to locate DR lesions from DR images in order to categorize them. DR must be recognized and treated as soon as possible to limit the risk of blindness. The manual diagnosis technique became useless as the severity of DR's effects increased. As a result, using computer-aided screen systems (CASS) to automate DR diagnosis saves effort, money, and time.

Al-Mukhtar et al. [5] integrate weakly-supervised localization techniques with automated detection to classify diabetic retinopathy. The model is divided into four phases, the first of which involves smearing the data set using a number of pre-processing techniques. Because this network has narrowed its focus exclusively on the optical disc region in stage two, any relatively incorrect predictions are avoided because exudates have the same color pixel as the optical disc. The network is given training data to categorize each label in the third stage. Finally, the layers of a convolution neural network are changed to focus only on the patient's eye. The framework addresses the technique of matching between two essential conceptions, and the classification problem is solved using the supervised learning approach.

Kumar et al. developed the novel Deep-in-Net technique in paper [6], which comprises of three basic phases and yields constellations with varying degrees of DR severity. These datasets are trained under supervision at the picture step. The Deep-in-Net generates the attentiveness maps for the suspected illness area. The approach can validate and discover depending on the aim.

P. Kaladevi et al., in article [7], 2021, Qureshi et al. utilizing active deep learning (ADL)-CNN, a 7-layered CNN design was suggested that automatically and simultaneously recognizes the five steps of DR with lesion localisation utilizing some ground-truth annotation fundus sample rather than the entire collection of training images. Before being fed into the algorithm for learning distinguishing qualities, the input fundus image was pre-processed to improve contrast within uniform-color space and augmentation approaches.

Yu Wang et al., (Firke et al, 2021) designed a paper [8] that can recognize DR without the assistance of a specialist. CNN-based deep learning algorithms are effective and accurate at picture classification. In this experiment, they compared the performance accuracy of an existing model. They improved the method's performance by adjusting parameters such as the number of convolution layers and the pooling layer optimizer.

In study [9], Piyush Jain et al. (Nderitu, et al, 2022) developed and evaluated a deep learning (DL) model for automated curation of grad capacity, retinal presence, retinal field, and single- and multilaterality. DL identifies laterality, retinal presence, retinal field, and gradability of DR screening images with high generality across centers and populations. For automatic picture curation in DR screening, DL models may be used. Early detection of sight-threatening DR (STDR) by retinal photography-based DR screening allows for quick referral and treatment, perhaps reducing the risk of mild vision loss.

Amit Sawant et al., (Raumviboonsuk, et al, 2019) presented one of the largest population-based clinical trials for the deep learning system on a system other than the one it was trained on in paper [10]. To achieve this external validation, it was directly compared to the screening program's actual graders from the same population.

In publication [11], Abhishek Punde et al. (Dai, et al, 2021) built an automated, interpretable, and verified system that grades DR from early to late stages, diagnoses retinal lesions, and provides real-time feedback on picture quality. With such qualities, DeepDR technology can improve picture collection quality, provide clinical references, and simplify DR screening. The DeepDR approach achieved high sensitivity and specificity in DR grading. Rather than simply producing a DR grading, it gives visual indicators that assist users in recognizing the presence and location of various lesion types. DeepDR was enhanced with lesion-aware and image quality subnetworks, which improved diagnosis performance and closely mirrored ophthalmologists' mental processes.

G. M. Shahariar et al. (Krause, et al, 2018) believe that reliable ground truth determination is a critical component of developing therapeutically applicable machine learning algorithms for use in the identification or screening of retinal illness in Paper [12]. The live adjudication process by several subspecialists results in a consensus grade and upgraded screening models, which improves algorithmic accuracy.

III. LITERATURE SURVEY DETAILS

PN	Short notes	Advantages	Disadvantages
[1]	Despite the fact that artificial intelligence (AI) has long enhanced the accessibility, affordability, and quality of healthcare, the FDA had never previously certified an autonomous AI diagnostics equipment. The most important test for an AI system is identifying diabetics with diabetic retinopathy (DR).	The AI system outperformed all previously stated superiority endpoints, with a picture ability rate of 96.1% and a sensitivity rate of 87.2%.	Due to selective dilatation, scalable clinical deployment may meet challenges.
[2]	Using the HOG, create an application to import and recognize humans in films. To recognize humans in films, the (Histograms of Oriented Gradients) approach is employed. The HOG Algorithm is used to recognize and count people in each frame of the movie.	Human detection accuracy is 81.23 percent on average across 10 videos, with a standard deviation of 10.95 percent.	The program is still in its early phases of development.

[3]	The proposed system localizes the damaged lesions on the retinal surface and classifies the five stages of DR into No-DR, mild, moderate, severe, and proliferative DR. Two deep learning-based models are included in the system. The first model (CNN512) took the entire image as input and classified it into one of the five DR phases. The second model identified and localized the DR lesions while using a recognized YOLOv3 model.	CNN512 and YOLOv3's fusion outperformed current state findings in categorizing DR images and pinpointing DR lesions, with an accuracy of 89%, sensitivity of 89%, and specificity of 97.3%.	The erroneous labelling of the photographs has an impact on the model's findings.
[4]	For the classification of diabetic retinopathy, the model blends weakly-supervised learning-based localization techniques with automatic detection.	Under loose oversight, technology achieved 0.954.	The network's ability to deliver dismal, tenebrous, dull data to the model will lower its effectiveness.
[5]	Convolutional neural networks (CNN) have been proposed as a way for identifying additional potential locations and detecting diabetic retinopathy. Deep-in-Net, a reliable sickness detection method, is used in conjunction with machine learning algorithms.	This strategy is useful for mapping attention.	The highest rate of accuracy is around 80-86%.
[6]	To enable automatic identification of the DR stage (ADL), a new multi-layer active deep learning architecture is proposed. When developing the ADL system, we used convolutional neural network (CNN) models to automatically extract features rather than handmade characteristics.	ADL-CNN architecture outperforms at recognizing the five DR severity levels and DR-related lesions on diverse fundus imaging photos.	It has been observed that the ADL-CNN approach has a computational difficulty when processing large volumes of data.
[7]	Convolution neural networks have been used to identify diabetic retinopathy. It conducted early image processing on the image, primarily picture resizing, pixel rescaling, and label encoder, while training a convolution neural network on the Apatos Blind Detection dataset. This convolution neural network model is then fed an image to determine whether or not the patient has diabetic retinopathy.	Our network design has achieved a satisfactory level of classification accuracy using dropout approaches.	The system is given test samples, but the actual goals are compared before presenting the model's error statistics.
[8]	Deep learning (DL) algorithms for grad ability classification, retinal presence, single and multiple output laterality, and retinal field for automated curation were designed and evaluated. DL efficiently identifies laterality, retinal presence, retinal field, and gradability of DR screening images with generalisation across centers and populations.	Despite considerable differences in image sensors, DR severity, and DR screening methodologies, study methods for sequence categorization based on DL models work well.	There is a retina present. Because there were so few non-retinal samples, specificity could not be confirmed with such certainty.
[9]	The accuracy of an expert has been obtained in the Diabetic retinopathy (DR) can be identified using deep learning algorithms. The goal of this study is to validate one such strategy on a large clinical population and compare its performance to that of human graders.	Deep learning significantly reduced the rate of false negatives (by 23%) across varied DR severity levels for diagnosing referable disease, albeit at the expense of slightly higher false positive rates (2%).	have an impact on illness prevention, progression, and consequences.
[10]	Retinal screening allows for the early detection and treatment of diabetic retinopathy. To simplify the screening method, we developed DeepDR, a deep learning system that can detect diabetic retinopathy in its early to late stages. DeepDR was trained in lesion recognition, grading, and real-time image clarity assessment using	The DeepDR approach achieved high sensitivity and specificity in DR grading.	More research is required to evaluate how successfully deep learning algorithms identify and predict the course of DR.

	466,247 fundus pictures from 121,342 diabetic patients.		
[11]	Adjudication can be used to quantify diabetic retinopathy (DR) grading errors based on each grader individually and the majority vote, as well as to design a better automated DR grading system..	When higher-resolution pictures were utilized as input, the algorithm's AUC for moderate or worse DR increased from 0.934 to 0.986. A small number of adjudicated consensus grades were employed as a tuning dataset..	When paired with higher-resolution pictures and a limited collection of adjudication consensus grades as a unifying dataset, the algorithm's AUC increased from 0.934 to 0.986 for moderate or worse DR.

Table 1 Literature Survey Details

IV. CONCLUSION

Diabetic retinopathy is one of the most common vision problems found in diabetics. Early diagnosis and accurate classifications are critical for proper and exact therapy. The basic methods used to diagnose and categorize diabetic retinopathy were addressed and analyzed in this study, which looked at a variety of research and survey articles. At each stage of the research, numerous strategies were tested, including feature extraction, pre-processing, and classification. It also highlighted a number of notable advances achieved by these algorithms. According to the survey, it may be more helpful to employ machine learning or the deep-learning technique for therapeutic goals such as reducing the progression of diabetic retinopathy in patients and allowing the ophthalmologist to speed subsequent retinal treatment. The growing prevalence of diabetic persons with DR has increased the requirement for developing alternative DR recognition methodologies to present procedures. The findings of this assessment will help researchers in this field advance their work by informing them of the methodologies and procedures currently used for DR detection and classification.

REFERENCES

[1] Abramoff, M.D., Lavin, P.T., Birch, M. et al. Pivotal trial of an autonomous AI-based diagnostic system for detection of diabetic retinopathy in primary care offices. npj Digital Med 1, 39 (2018).

[2] T. Surasak, I. Takahiro, C. -h. Cheng, C. -e. Wang and P. -y. Sheng, "Histogram of oriented gradients for human detection in video," 2018 5th International Conference on Business and Industrial Research (ICBIR), 2018, pp. 172-176.

[3] Wejdan L. Alyoubi, Wafaa M. Shalash, Maysoon F. Abulkhair, Diabetic retinopathy detection through deep learning techniques: A review, Informatics in Medicine Unlocked, Volume 20, 2020, pp. 1-11.

[4] Alyoubi, W. L., Abulkhair, M. F., & Shalash, W. M. (2021). Diabetic Retinopathy Fundus Image Classification and Lesions Localization System Using Deep Learning. Sensors, 21(11), 3704, pp. 1-22.

[5] Al-Mukhtar, M., Morad, A.H., Albadri, M. et al. Weakly Supervised Sensitive Heatmap framework to classify and localize diabetic retinopathy lesions. Sci Rep 11, 23631 (2021).

[6] Kumar, KG & Karunakara, K & GS, Dr.Thyagaraju & Dixit, Sunanda. (2021). Detection of Diabetic Retinopathy using Deep Mining. IOP Conference Series: Materials Science and Engineering. pp. 1-9.

[7] Qureshi, I., Ma, J., & Abbas, Q. (2021). Diabetic retinopathy detection and stage classification in eye fundus images using active deep learning. Multimedia Tools and Applications, 80(8), pp. 11691–11721.

[8] S. N. Firke and R. B. Jain, "Convolutional Neural Network for Diabetic Retinopathy Detection," 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS), 2021, pp. 549-553.

[9] Nderitu, P., Nunez do Rio, J.M., Webster, M.L. et al. Automated image curation in diabetic retinopathy screening using deep learning. Sci Rep 12, 11196 (2022), pp. 1-12.

[10] Raumviboonsuk, P., Krause, J., Chotcomwongse, P., Sayres, R., Raman, R., Widner, K., Webster, D. R. (2019). Deep learning versus human graders for classifying diabetic retinopathy severity in a nationwide screening program. Npj Digital Medicine, 2(1), pp. 1-9.

[11] Dai, L., Wu, L., Li, H., Cai, C., Wu, Q., Kong, H., Jia, W. (2021). A deep learning system for detecting diabetic retinopathy across the disease spectrum. Nature Communications, 12(1), pp. 1-11.

[12]Krause, J., Gulshan, V., Rahimy, E., Karth, P., Widner, K., Corrado, G. S., Webster, D. R. (2018). Grader Variability and the Importance of Reference Standards for Evaluating Machine Learning Models for Diabetic Retinopathy. Ophthalmology, 125(8), pp. 1264–1272.

[13]World Health organization: WHO, "Diabetes," Who.int, May, 2019. https://www.who.int/health-topics/diabetes.

[14]"Mayo Clinic – Mayo Clinic", MayoClinic.org, 2021. https://www.mayoclinic.org/ (accessed Feb. 10, 2021).

[15] "Latest Medical News, Clinical Trials, Guidelines – Today on Medscape," Medscape.com, 2021. https://www.medscape.com/.