Advancing Healthcare: Unlocking the Potential of CNN Algorithm for Diabetic Retinopathy Detection

Dr. P. Balashanmuga Vadivu., Ph.D. Associate Professor[1]
shanmugavadivup@mahendra.info

Dr. D. Chitra Ph.D., Professor[3]
chitravalli2000@gmail.com

Monisha. B[2]
nishaela131218@gmail.com
M.E. Communication Systems Engineering,
Department Of Electronics and Communication Engineering,
Mahendera Engineering College, Tiruchengode Highway, Mahendhirapuri, Namakkal-637503.

Abstract—To decrease the occurrence and advancement of Diabetic-Retinopathy (DR), it is essential to strictly regulate blood glucose and blood pressure. Patients with diabetes mellitus are not just monitored when symptoms appear; rather, this is based on established protocols. The duration between checkups is determined by the patient's DR stage, which can be mild, moderate, or severe (non-proliferative DR vs. PDR). Diabetic-Macular-Edoema (DME) is the leading cause of blindness in people with diabetes. Retinal Image Analysis for the Diagnosis of Ocular Diseases using Fuzzy Logic Image Processing, Segmentation of Optic Discs, and Blood Vessels. According to randomized studies conducted at many centers, intravitreal ranibizumab injections followed by focused laser photocoagulation now produce the best visual outcomes for DME. It appears that the results achieved with bevacizumab and ranibizumab are very similar. This method seems to slow the growth of DR and cure DME at the same time. Intravitreal steroid medication and focused laser therapy may be helpful for certain individuals, but they come with an increased risk of glaucoma and cataracts. An rise in intraocular pressure, which is located inside the retina, can lead to the neurodegenerative eye disease known as glaucoma. Due to its status as the second leading cause of blindness globally, a delayed diagnosis might result in total blindness. The architecture of Convolutional- Neural-Network (CNN) is reminiscent of the human brain's connective tissue and was influenced by the visual cortex. In addition to improved accuracy, the CNN algorithm can make predictions much more quickly.

***Index Terms*—Deep Learning, DL, Diabetic Retinopathy, DR, Optic Disc Segmentation, Fuzzy Logic, Glucose Level, Retinopathy, Glaucoma**

I. INTRODUCTION

A condition where the retina is damaged as a result of diabetes is called diabetic retinopathy or diabetic eye disease [1]. Blindness may result in due time. This eye condition is a symptom of the systemic illness diabetes, which affects as many as 80% of people with diabetes over 20 years or more [2]. Often, there are no early indicators of diabetic retinopathy. There may be no symptoms for a while, even for macular edoema, which can lead to fast vision loss. However, impaired vision is a common symptom of macular edoema, which can make daily tasks like reading and driving difficult for affected individuals [3][4]. Depending on the individual, daytime eyesight might improve or worsen. In the first stage of diabetic retinopathy, known as non-proliferation retinopathy, individuals would have perfect vision and no symptoms whatsoever [5]. Microaneurysms can be observed in fundus photography, which is the sole means to diagnose NPDR. To view what's behind the eye, fluorescein angiography will be performed if eyesight is impaired. Ischemia, in which blood vessels in the retina are narrowed or stopped, is easily visible [6].

Any point in the NPDR process can bring about macular edoema, a condition in which the contents of blood vessels seep into the macular area. Macular edoema is characterized by a loss of sharp vision and a difference in the brightness or contrast between the two eyes. Macular edoema causes vision loss in 10% of diabetic people. The Rigidity of Light Macular edoema causes a thickening of the retina as a result of fluid buildup; this thickening can be seen on tomography [7]. In the second stage of proliferative diabetic retinopathy, aberrant new blood vessels develop behind the eye. These could rupture, hemorrhage, and distort vision due to their fragility [8]. A considerably heavier blood loss, which obstructs eyesight, frequently follows these spots a few weeks or days later. A person may lose the ability to see in one eye altogether in the most severe instances. The time it takes for the blood to drain from the interior of the eye can vary greatly, taking anyplace from a couple of days to months—or even years. On rare occasions, the drainage may not occur at all. Large hemorrhages like this may occur several times, most frequently as you sleep [9].

High blood glucose levels are a hallmark of diabetes mellitus, a chronic condition in which the pancreas fails to release enough insulin to regulate blood sugar levels. The leading cause of blindness in those younger than 50 is diabetes. Diabetic retinopathy (DR) is a direct result of diabetes mellitus and occurs when glucose builds up in the blood vessels that supply the eye. This leads to inflammation and possible leakage of blood or fluids, which can inflict serious damage to the eye. Central thickening of the retina is the most common cause of the harmful vision loss caused by DR [10]. The following figure Fig.1 the five potential phases of DR development.

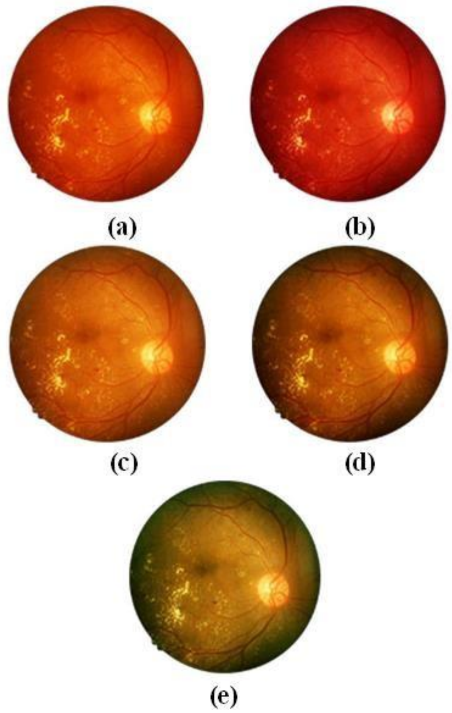

Fig.1 Potential Phases of DR Development (a) Normal, (b)Minimal, (c) Moderate, (d) High and (e) Proliferate

Early identification is crucial for preventing problems linked to chronic illnesses like diabetes. Scarring or bleeding within the retina, and eventually blindness, can result from abnormal blood vessel development in the retina, a possible complication of DR. This can lead to a gradual deterioration of eyesight, eventually leading to complete blindness in severe cases. Worldwide, DR accounts for 2.6% of all cases of blindness. The most significant risk factors linked to the development of DR include the duration of diabetes, elevated haemoglobin A1C, and hypertension. In order to catch DR early, it is essential that diabetic individuals undergo screening regularly. A clinician would often look at retinal imaging to see what kinds of lesions are present and how they appear in order to diagnose DR. Lesion types often include micro-aneurysms (MA), hemorrhages (HM), soft exudates, and hard exudates. At the first stage of diabetic retinopathy, known as micro- aneurysms (MA), tiny red spherical dots appear on the retina as a result of a weakening of the vessel walls. Sharp borders that are not larger than 125 micrometers in diameter characterize the dots. Although micro-aneurysms can be further subdivided intosix categories, therapy is consistent across all of them.
(i) In contrast to micro-aneurysms, big patches on the retina having uneven border diameters of more than 125 micrometers are diagnostic of haemorrhages (HM). There are two types of haemorrhages: those with superficial (or "ame") and deep (or "blot") spots.
(ii) Yellow patches on the retina called hard exudates, which are actually the result of plasma leakage, are evident. They are sharply bordered and extend over the outer layers of the retina.
(iii) Visible white ovals in the retina called soft exudates are caused by enlargement of the nerve fibers.

II. RELATED STUDY

In humans, diabetic retinopathy comprises a condition that damages the retina and can lead to total blindness [11]. To prevent total blindness, diabetic retinopathy must be detected early. Diabetic retinopathy can be detected using a battery of physical examinations, including a visual acuity test, pupil dilation, and optical consistency tomography. Nevertheless, it might have an impact on the patients and is time-consuming. This research uses a machine learning method to identify cases of diabetic retinopathy in humans. As an example, the optical disc diameter, lesion-specific characteristics (micro-aneurysms, exudates, or presence of hemorrhages), and a current Diabetic Retinopathy dataset are all used by the proposed method's classification algorithms. In order to make a definitive determination about whether or not diabetic retinopathy was present, the characteristics were extracted. Logistic Regression and Decision Trees were utilized by the prescribed system. Machine learning with support vectors to make predictions. Results were 88% accurate using the suggested strategy, which is a significant improvement over previous efforts. In addition, the suggested technique outperforms the current result by a significant margin; the precise score is 97% and the recall score is 92%, respectively, compared to 72% and 63%, or an average improvement of over 25% in both categories, demonstrating anenormousness of the suggested approach [11].

Retinopathy, or diabetic eye disease, is the most common consequence of diabetes. Prolonged illness, inadequate glucose management, and hypertension are the primary risk factors [12]. Nonetheless, additional variables, including glycemic fluctuation or genetic inheritance, likely play a significant role in explaining the vulnerability to DR development, as there is a substantial risk variance. The idea that DR independently predicts micro-vascular and macro-vascular problems is another crucial one. Therefore, while assessing the risk for cardiovascular disease of a diabetic individual, it is important to include the existence of DR. Cognitive impairment is a new consequence of type 2 diabetes, and evaluating retinal neuro- degeneration might help find those who are at risk for it. Knowing if DR is present has therapeutic consequences when examining a diabetic person. Here, a quick drop in blood glucose levels could lead to DR getting worse. To summarize, this article presents a comprehensive evaluation of the literatureregarding the significance of DR in the overall care of diabeticpatients [12].

A persistent illness defined by persistently high blood sugar levels is diabetes [13]. Diabetic retinopathy (DR) is a major consequence of diabetes that causes a variety of symptoms, including impaired or lost vision, due to the blocking of the small blood capillaries in the retina. In order to manage symptoms and maybe slow the disease's course, early discovery and diagnosis are vital. Ophthalmologists rely on fundus photography as a reliable and low-cost diagnostic tool. The distribution of different types of DR is severely skewed in fundus photography datasets. Here, we reveal two-stage Deep Convolutional Neural Networks architecture that, when trained with a ResNet-50 that has been fine-tuned, can reliably categorize DR as mild, moderate, or severe. Additional classification for moderate DR was done using a ResNet-18 that had been fine-tuned, and for severe DR, a ResNet-50 that had also been fine-tuned was employed. The suggested design has a pre-processing step that includes data augmentation and picture scaling. Over the course of 10 epochs, 3,648 fundus pictures from the Kaggle APTOS 2019 datasets were subjected to training as well as 5-fold cross validation. With a precision of 91% in the first stage, 90% in the second sub-stages, and 80% overall, the suggested design outperformed the state-of-the-art architectures [13].

Using vascular characteristics like as vessel density, inter- capillary spacing, vessel diameter index, total vessel length, vascular architecture, and extent of the foveal vascular zone, recent investigations on the involvement of OCTA in DR have been conducted [14]. In therapeutic trials, these numerical indicators might be able to pick up on shifts in DR severity and course. In addition to its potential use in predicting visual prognosis, OCTA has the added benefit of being a non-invasive imaging technique for detecting diabetic macula ischemia. One of OCTA's numerous drawbacks in DR is the difficulty it has in segmenting the superficial as well as the deep capillary plexus. Another is that it may not be useful in diabetic macula edoema due to the existence of cystic spaces, which can alter the picture results. The identification of anterior segment ischemia along with iris neo-vascularization linked to proliferative DR and thedanger of neo-vascular glaucoma are two potential future uses of OCTA in the anterior segment [14].

The damaging consequences of diabetes in the eyes lead to diabetic retinopathy. Another condition that requires prompt diagnosis is diabetic retinopathy [15]. Blindness can develop if it is not addressed promptly. Diabetic retinopathy is predicted to affect one-third of almost half a million diabetics' people by the year 2200. Several promising approaches for illness diagnosis using deep learning have been put forward. Unlike previous research, this one proposes a deep learning-based approach to automatically detect and classify diabetic retinopathy lesions, regardless of datasets. Gathering information about diabetic retinopathy from various sources is the initial step in the suggested procedure. Faster RCNN can identify lesions and highlight the areas of interest. The second stage involves classifying the pictures using the attention and transfer learning process. The approach achieved an area under the curve (AUC) of 99.9% and an accuracy of 100% on the Kaggle dataset, while on the MESSIDOR dataset, it was 99.1%. There is a noticeable improvement in the quality of the results when compared to those found in the literature [15].

III. METHODOLOGY

Among the many avoidable causes of blindness, diabetic retinopathy ranks high among the most debilitating chronic illnesses. A significant investment in screening programmes, particularly automated screening programmes, is necessary to obtain early detection of diabetic retinopathy, which allows for prompt treatment. Strong, effective algorithms for processing and analyzing images are necessary for automated screening programmes to function. In order to identify diabetic retinopathy in its early stages, this study reviews the current research on digital image processing as it pertains to fundus pictures. Pathologies of diabetic retinopathy were further classified into many classes. There is an alarming increase in the number of instances of glaucoma, a condition that causes permanent damage to the eyesight. The key to preventing more visual field loss is early identification, which allows for promptintervention.

In order to identify glaucoma, fundus imaging can be used to examine the optic nerve head, specifically the optic cup or disc borders. The incidence of glaucoma is steadily increasing across the world, and fundus imaging offers a non-invasive, cost-effective way to detect the disease. The key to preventing more visual field loss is early identification, which allows for prompt intervention.

The most common eye diseases that cause blindness or severe vision impairment are glaucoma and cataract. Because they are both associated with ageing, the two diseases can coexist. Glaucoma surgery can hasten the development of cataracts, and cataracts can hasten the development of glaucoma. When glaucoma and cataracts coexist, the former may prompt a patient to seek medical attention because of the cloudy vision as well as white pupil that result from cataracts, while the latter may cause slow but steady vision loss that the patient is unaware of until the latter is well advanced.

Blood vessel alterations and diabetic retinopathy are the results of diabetes. The picture will go through the usual steps of image processing, which include acquiring the image, pre- processing it, extracting features from it, and finally, accurately identifying the disease. Currently, the technology is limited to detecting a single ailment. We have presented a method that can identify any kind of eye illness using just one system. Our research intends to apply CNN algorithm to automated eye illness identification based on the categorization of retinal pictures. This will be done since retinal images are among the most essential medical references for diagnosing conditions such as glaucoma, cataracts, and diabetic retinopathy. The following figure Fig.2 shows the block diagram of the proposedsystem.

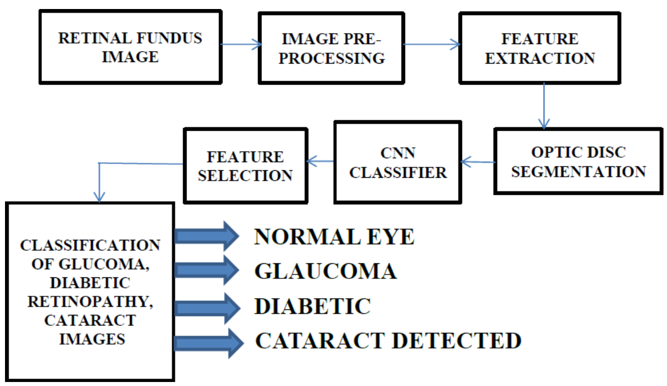

Fig.2 Block Diagram of Proposed System

(i) Acquiring Images: A dataset contains four distinct forms of retinopathy: hard exudates, soft exudates, hemorrhages, and red tiny spots. Pick a picture to categorize from that set.

(ii) Pre-processing: When an image is expected to be three- dimensional, it is transformed into gray-scale during pre- processing. This is done to accomplish two-plane conversions.

iv) Image Data Input: The first step is to snap an image with the enlargement and then adjust its size to fit the needs. Before feeding it into the CNN model, the input data must be pre- processed to make it more suitable for the model. The image's noise is either eliminated or significantly diminished. Some aspects have been improved. And lastly, the imagery is gray- scale.

(iv) Enhancement: Bring out more details in the photos that were shot with the original camera. A lower signal-to-noise ratio is achieved by filtering pictures into gray-scale versions from which certain characteristics are extracted. The goal of image enhancement is to improve the visual quality of digital photographs by applying various filters and effects, such as sharpening or smoothing them out. When it comes to processing digital images, this is a crucial subject. It can aid in the correct extraction of information from the improved pictures by both humans as well as computer vision systems. The enhancement technique increased the visual quality and certain picture qualities, including contrast, brightness, signal- to-noise ratio, resolution, edges sharpness, as well as color correctness. Numerous approaches for improving images have emerged in recent years, all built on top of digital image processing. Particularly during the segmentation step, the improved image will yield valuable data for post-processing. Medical representation research, analysis of satellite imagery and every other industry makes use of picture enhancement. Improving gray-scale pictures through histogram transformation is a cornerstone procedure that paves the way for more advanced operations like detection and identification. Although there are a number of well-known techniques for improving a picture's contrast, the majority of them rely on heuristics derived from in-depth expert knowledge of image processing, such as histogram equalization and contrast adjustments. Therefore, due to their complex formulations, these methods need a substantial amount of analysis and calculation. By enhancing the image's information density, histogram equalization affects the histogram in a roundabout way. Numerous related domains rely heavily on optimization, including robotics, AI, operational research, and others. The goal is to discover the optimal solution to an optimization issueas quickly as feasible.

(v) Threshold: Cell segmentation is employed for thresholds, which can yield precise outcomes. One method of segmenting images is image thresholds, which separates an image's foreground and background. The pixel values assigned by the implemented technique match the given threshold values. The threshold is performed on gray-scale images in computer vision. When using basic thresholds, each pixel value above a predetermined threshold is set to a default value. It checks the values of the pixels against a predetermined threshold. Here arethe segmented photos based on threshold values after pixel separation.

(vi) GLCM: The gray-level co-occurrence matrices (GLCM), often called the gray-level spatial dependency matrix, is a statistical tool for analyzing texture that takes pixel relationships into account. By generating a GLCM followed by extracting statistical metrics from it, the GLCM functions characterize an image's texture by calculating the frequency of pairs of pixels with given values and in a defined spatialrelationship.

(vii) Extraction of Features: The purpose of feature extraction aims to identify melanoma by extracting picture attributes that describe its dermatological characteristics. Melanoma characteristics are used by clinicians. While choosing the characteristics, it is crucial to consider the diagnostic approachthat will be used.

(viii) Segmentation: Recently, skin cancer image segmentation has emerged as a major area of focus for R&D efforts. When describing or classifying images, segmentation comes into play as a crucial challenge in digital image processing. Skin lesion segmentation can be aided by using a variety of form, brightness, color, and texture features.

IV. RESULTS AND DISCUSSIONS

People with diabetes are at increased risk for developing diabetic retinopathy, an eye disorder that can lead to blindness or severe visual loss. The disease impacts the blood vessels located in the retina, which is the rear layer of tissue in the eye that is sensitive to light.
- Diabetic retinopathy in its first stage: mild and non-proliferative.
- Modest non-proliferative diabetic retinopathy is the secondstage.
- Serious non-proliferative diabetic retinopathy is the thirdstage.
- Diabetic retinopathy in its advanced stages

The exceptional performance of convolutional neural networks when fed audio, voice, or visual signals sets them apart from other types of neural networks. There are mostly three kinds oflayers in them:
- Fully Connected (FC) Layer
- Pooling Layer
- Convolution Layer

Starting with the convolution layer, a convolution network is constructed. Each convolution layer must be followed by a fully-connected layer, even though additional pooling or convolution layers are possible following convolution layers. As the number of layers in a network of convolution neural networks increases, the network's intelligence grows, enabling it to identify increasingly complex scenes. Colors and borders are the primary focuses of the lower levels. Moving the picture data up the CNN's layers allows it to pick up on the object's bigger features and forms until it finds what it's looking for. The bulk of a convolutional neural network's (CNN) processing happens in its central building block, the convolutional layer. The three most essential parts are a feature map, a filter, as well as a data input. For the sake of argument, let's say the input is a color picture, which is a 3D matrix of pixels. The three dimensions of the input will be height, width, and depth, much like an RGB picture. As an additional tool, we have a feature detector— sometimes called a kernel or a filter—that scans the image's receptive fields to determine if the feature is noticeable. A convolution describes this procedure. The feature detector is an array of weights that represents a portion of the picture in two dimensions (2-D).

The size of the receptive field is dictated with the filter size, and it is typically a 3x3 matrix; however there is considerable variation in size. The next step is to set the filter to a selective area of the image; after that, we'll calculate the dot product of the filtered as well as raw input pixels. An output array is subsequently supplied with this dot product. The procedure is repeated until the kernel has scanned the whole picture, after which the filter moves by one stride. A sequence of dot products from the input and the filter provide what is called as a convolved feature, activation map, or feature map ultimately. After each convolution phase, a CNN applies the linear units' correction to the feature map, which introduces non-linearity to the model. Following the first convolution layer is an option, as we indicated before. This allows subsequent layers to access the pixels inside the receptive fields of earlier layers, potentially leading to a hierarchical CNN structure. Take the case of trying to identify whether a picture has a bicycle as an example. The bicycle may be seen as more than the sum of its components.

Things like a frame, handlebars, wheels, pedals, and so on make it up. The CNN's feature hierarchy is like a bicycle: the pieces individually make up a lower-level pattern, while the parts combined constitute a higher-level pattern. Pooling layers, also known as down sampling, carry out dimensional reduction to decrease the quantity of input variables. While both the convolutional layer and the pooling operation use a filter to process the input data, the pooling operation differs in that it does not use weights. Rather, the values in the receptive field are aggregated by the kernel, which then populates the output array. The two most prevalent forms of pooling are maximum and averaged. The following figure, Fig-3 represents the input image of the diabetic retinopathy detection scheme.

Fig.3 Input Image

The following figures, Fig-3 and Fig-4 represent the pre- processing and boundary detection stages of the proposed scheme.

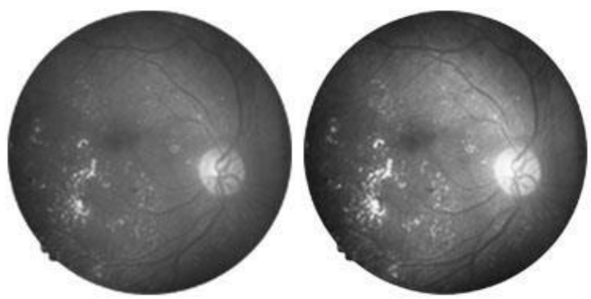

Fig.4 Pre-Processing (a) Grayscale Conversion and (b)Pixel Evaluation

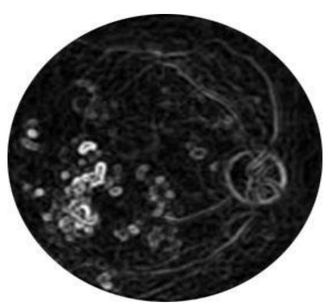

Fig.5 Boundary Detection

The following figure, Fig-6 represents the image segmentation and classification process of the diabetic retinopathy detection scheme.

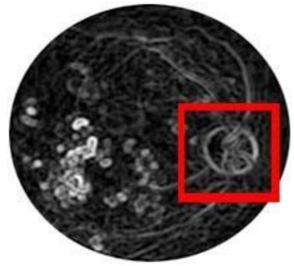

Fig.6 Segmentation and Classification

The following figure, Fig-7 represents the prediction accuracy of the diabetic retinopathy detection scheme called CNN, in which it is cross-validated with the conventional learning process called SVM to evaluate the efficiency of the proposed scheme. And the same is depicted into the following table, Table-1 in descriptive manner.

Table-1: Prediction Accuracy

Iterations	SVM (%)	CNN (%)
50	86.26	95.49
75	86.34	95.87
100	86.29	95.62
125	86.41	95.71
150	86.59	95.78
175	86.60	95.82
200	86.67	95.86
225	86.74	95.90
250	86.82	95.94

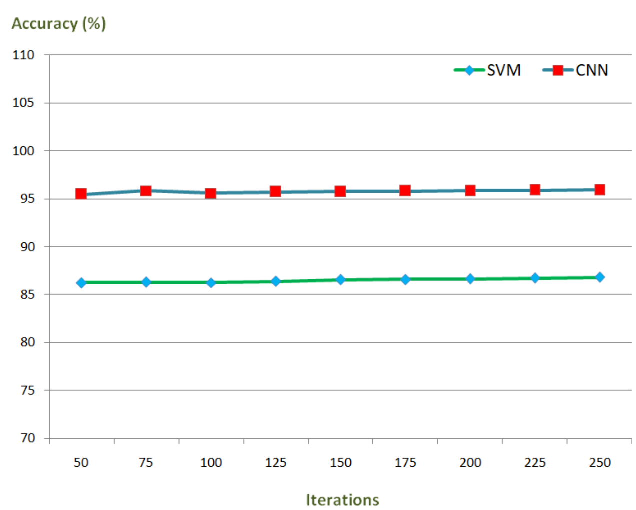

Fig.7 Prediction Accuracy

V. Conclusion and Future Scope

Our automated imaging technique for detecting HEs was developed and verified prospectively. By utilizing a statistical classification for colour and a Kirsch operator for edge sharpness, the system is able to detect HE lesions. We found that the technique works great as an adjunct to DR screening and might be useful for ophthalmologists in their work. Improvement and classification of the DR stage with the use of DL-based methods for lesion identification across various fundus images. Manual diagnosis, which must follow screening and is sometimes a time-consuming process susceptible to ophthalmologists' bias, is the primary concern discussed in the papers that were examined. In addition, the variances in fundus images that may be utilized for indication evaluation are limited due to dataset constraints. Deep Learning has made retinal scan analysis quicker, more inclusive, and more generalizable; yet, the criteria employed to evaluate the results and datasets are still biased and imbalanced between researches, despite this progress. Classifying DR is essential, but there may be research opportunities to understand its varied causes as well. For example, some changes in lesions and other unspoken signs may suggest the likelihood of getting DR. Since the presence of Diabetic Macular Edoema (DME) is strongly indicative of the retinal development of DR, investigating this condition might lead to further avenues of inquiry. Researchers may be able to better understand the origins of retina-based disorders with the aid of these improvements, which make it easier to generalize DL-based models and evaluate a broader variety of symptoms and signs. Finally, Transformers alleviated the problems associated with non-generalizability by introducing more explainable approaches. Patching and embedding fundus pictures with various context enrichment methodologies have improved the detection of hidden signs.

REFERENCES

1. Stephen H. Sinclair and Stanley S. Schwartz, "Diabetic Retinopathy–An Underdiagnosed and UndertreatedInflammatory, Neuro-Vascular Complication of Diabetes", Frontiers in Endocrinology,https://doi.org/10.3389/fendo.2019.00843, 2019.
2. Filippo Arcadu, Fethallah Benmansour, et al., "Deep learning algorithm predicts diabetic retinopathy progression in individual patients", npj Digital Medicine, https://doi.org/10.1038/s41746-019-0172-3, 2019.
3. María L. Rodríguez, Salvador Pérez, et al., "OxidativeStress and Microvascular Alterations in Diabetic Retinopathy: Future Therapies", Oxidative Medicine and Cellular Longevity, https://doi.org/10.1155/2019/4940825, 2019.
4. Yung-Hui Li, Nai-Ning Yeh, et al., "Computer-Assisted Diagnosis for Diabetic Retinopathy Based on Fundus Images Using Deep Convolutional Neural Network", MobileInformation Systems, https://doi.org/10.1155/2019/6142839, 2019.
5. Kendrick C. Shih, Alfred S. K. Kwong, et al., "Diabetic retinopathy screening during the coronavirus disease 2019 pandemic", Eye, https://doi.org/10.1038/s41433-020-0928-7, 2020.
6. Prof Paisan Ruamviboonsuk, Richa Tiwari, et al., "Real- time diabetic retinopathy screening by deep learning in a multisite national screening programme: a prospective interventional cohort study", The Lancet Digital Health, https://doi.org/10.1016/S2589-7500(22)00017-6, 2022.
7. Niloy Sikder, Mehedi Masud, et al., "Severity Classificationof Diabetic Retinopathy Using an Ensemble Learning Algorithm through Analyzing Retinal Images", Symmetry, https://doi.org/10.3390/sym13040670, 2021.
8. Charles C. Wykoff, et al., "Management of Diabetes- Related Retinopathy ", ADA Clinical Compendia, https://doi.org/10.2337/db20191-11, 2019.
9. Dimple Nagpal, S.N. Panda, et al., "A review of diabetic retinopathy: Datasets, approaches, evaluation metrics and future trends", Journal of King Saud University - Computer andInformation Sciences,
10. https://doi.org/10.1016/j.jksuci.2021.06.006, 2022.
11. Shradha Dubey and Manish Dixit, "Recent developments on computer aided systems for diagnosis of diabetic retinopathy: a review", Multimed Tools Appl, https://doi.org/10.1007/s11042-022-13841-9, 2023.
12. S M Asiful Huda, Ishrat Jahan Ila, et al., "An Improved Approach for Detection of Diabetic Retinopathy Using Feature Importance and Machine Learning Algorithms", 7th International Conference on Smart Computing & Communications, DOI: 10.1109/ICSCC.2019.8843676, 2019.
13. Olga Simó-Servat, Cristina Hernández, et al., "Diabetic Retinopathy in the Context of Patients with Diabetes", Ophthalmic Res, https://doi.org/10.1159/000499541, 2019.
14. Stephen Cahoon, Mohamed Shaban, et al., "Diabetic Retinopathy Screening Using A Two-Stage Deep Convolutional Neural Network Trained on An Extremely Un- Balanced Dataset", SoutheastCon, DOI: 10.1109/SoutheastCon48659.2022.9764079, 2022.
15. Kai Yuan Tey, Kelvin Teo, et al., "Optical coherence tomography angiography in diabetic retinopathy: a review of current applications", Eye and Vision,https://doi.org/10.1186/s40662-019-0160-3, 2019.
16. Abdüssamed Erciyas and Necaattin Barışçı, "An EffectiveMethod for Detecting and Classifying Diabetic Retinopathy Lesions Based on Deep Learning", Computational and Mathematical Methods in Medicine, https://doi.org/10.1155/2021/9928899, 2021.