International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 02 Issue: 06 June 2024
Page No: 1646- 1651
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2024.0226

A Study on Effective Diabetic Retinopathy Using Deep Learning Approach

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Abstract

The goal of the project is to apply machine learning and deep learning approaches to diagnose diabetic retinopathy (DR). Diabetic retinopathy (DR) is one of the most notable and important microvascular consequences of diabetes mellitus. This degenerative disorder affects the retina and might cause blindness if therapy is not received in a timely manner. By having a complete grasp of the route physiology, acquiring a prompt diagnosis, and employing effective management approaches, the effects on the affected individuals can be minimised. The IDRID dataset and AGAR300 Dataset retinal pictures are used to identify the DR utilising a variety of manual engineering and end-to-end learning-based techniques. Early disease management depends on the identification of the mild stage. Similarity measurements are important in many data mining techniques. To enable the application of Haar Wavelet Transform algorithms (HWT) on non-standard databases, such as databases of financial time series, their similarity measure must be devised. The work focuses on a simple yet efficient approach that may be used to rapidly determine the degree of similarity between time series stored in large datasets. The goal of this work is to employ end-to-end deep ensemble networks to identify every stage of drug resistance. The results demonstrate that the suggested strategy works better than cutting-edge techniques. Pre-processing methods like as data augmentation, which increases the amount of training instances, and data normalisation, which accurately predicts classification, are necessary to provide the best mass image dataset for training models. Thus, the most recent CNN models (AlexNet, VggNet, GoogleNet, and ResNet) might be trained to identify the minute variations among the picture classes for DR Detection. Adopting hyper-parameter tuning with transfer learning techniques has shown experimental findings to be more accurate than non-transferring learning approaches in classifying DR images. It operates on the basis of the Orthonormal decomposition of the time series into the Haar basis. We demonstrate that this technique can produce estimates of the local slope of the time series across a variety of multi-resolution stages. The Haar representation and similar representations generated from it are suitable for direct comparisons, such evaluating the correlation product. We show that there is a strong correlation between the distance between such representations and the subjective sense of likeness between the time series. We examine the trade logs to verify the reliability of the subjective standards and discover robust associations.

Keywords: *Diabetic Retinopathy (DR), IDRID, Haar-Wavelet Transform (HWT), Time Series, Sign Representation, Convolutional Neural Networks (CNN).*

1. Introduction

Blindness has several important causes, one of which being diabetic retinopathy (1DR). A diabetic patient's retinal blood vessels are damaged by DR. Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR) were the two main forms of DR [9]. The early phases of the DR were referred to as NPDR, and they were further separated into three levels: mild, moderate, and severe. One Microaneurysma (MA), a tiny red dot that is round in shape and located at the terminal of

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blood vessels, is present in the moderate stage. The MAs rip into deeper layers and create a flame-shaped haemorrhage in the retina at the moderate stage. at each of the four quadrants, there are over 20 intrareticular haemorrhages at the severe stage. There is also noticeable intrareticular microvascular anomalies and distinct venous bleeding [10]. PDR is the more advanced stage of DR that causes neo vascularization, which is the spontaneous growth of new blood vessels on the inner surface of the retina in the form of functioning microvascular networks [11]. By 2025, there were projected to be 592 million DR sufferers worldwide, up from 382 million [12]. Individuals with diabetes are vulnerable to neurovascular issues that may lead to diabetic retinopathy and/or diabetic macular edoema (DME). Researchers found that 25% of individuals had non-proliferative diabetic retinopathy (NPDR) five years after receiving a diabetes diagnosis, 60% had it 10 years later, and 80% had it fifteen years later [13-16]. As per the findings of these studies, the prevalence of proliferative diabetic retinopathy (PDR) varied between 2.5% and 15.5% among individuals diagnosed with diabetes mellitus for a duration of fifteen years or more. Optometrists are the only medical professionals who may noninvasively assess systemic disease-related physical damage to blood vessels in the human body. This underlines the significance of closely monitoring all diabetic patients and collaborating with endocrinologists or primary care physicians (PCPs) to assist in their management [17-19]. Patients diagnosed with type 1 diabetes are advised by optometrists to get a thorough dilated eye examination no later than five years from the commencement of the disease. Patients with type 2 diabetes should have a comprehensive dilated eye examination both at the time of diagnosis and annually thereafter. Women who have previously been diagnosed with type 1 or type 2 diabetes, either before becoming pregnant or during the first trimester of pregnancy, should have a comprehensive dilated eye examination [20-22].

Study is about?

In most cases, patients with NPDR have different-sized hemorrhages, venous looping or beading, intraretinal microvascular abnormalities (IRMAs), hard exudates, soft exudates (cotton wool patches), and microaneurysms (MAs). Loss of intramural pericytes has damaged the retinal capillaries, resulting in the formation of MAs, which are saccular outpouchings [23-27]. Hemorrhages could occur through capillary walls progressively deteriorating and breaking up. IRMAs are either preexisting vessels with proliferation endothelial cells traveling through nonperfusion regions or new blood vessels formation within the retina [28]. The presence of IRMA signals ischemia and serves as a trigger for neovascularization. Severe retinal hypoxia is the cause of venous looping and beading, which represent a higher risk of neovascularization progression. When you have a diabetic patient in your chair, it is critical to learn as much as you can about their health [29].

2. Problem Definition

The most common impairment among living people was blindness, and diabetes is one of the main causes of blindness. The DR detection systems have longer execution times in addition to increased implementation costs. Thus, methods based on deep learning are created to address these problems. AlexNet, VggNet, GoogleNet, and ResNet are used by CNN [1] for DR image categorization. In this approach, the variability in morphological and other picture parameters, such as look, colour, and texture, was enhanced for recognising genuine haemorrhages of candidates. The accuracy of VggNet's model was good in comparison to other models. However, it performs poorly in terms of classification accuracy and lacks fundus images, which causes problems with data augmentation and normalisation. CNN [2] lowers the likelihood of vision loss. It is also a very time- and money-efficient procedure. There was no human expert involved in the adjudication of the labels used in this training and validation set, hence they were not interpretable. DCNN [3] provides high-performance, low-latency interference medical image detection and segmentation. Additionally, it makes advantage of semantic segmentation of fundus pictures, which may improve NPDR's accuracy and efficiency.As a result, the training process takes longer, there are more imbalances, and the resulting model is more complicated. CNN [4] has superior specificity and sensitivity and can identify all stages of DR with excellent detection accuracy. However,

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for the last step of decision-making, qualified specialists are required.More reliable results in DR related feature recognition and DR severity diagnosis are obtained with hierarchical multi-task learning [5].However, it is unable to encode the changes in light, rotation, and scale. DLSBVM [6] reduces the mistakes in incorrectly identifying vessel pixels from non-vessel images by utilising several layers. Furthermore, it enhances the image's contrast and eliminates noise from photos taken under various lighting conditions. However, because the margins did not emerge due to the difference in picture intensity between the vessel and backdrop, the best blood vessels were overlooked. Higher convergence rates are provided by DRISTI [7], which may increase the screening rate for DR patients. However, the dataset they utilised for this experiment was not balanced for the distribution of classes, and the system's implementation cost was relatively expensive. Back-propagation neural network architecture and a poorly supervised learning technique were used in the creation of CNN [8], which had certain advantages over automatic DR detection.The maintenance cost was expensive since it makes use of many filter algorithms and network settings. The recently established technique of retinopathy detection overcomes these obstacles.

Stage 1: MILD Non-Proliferative diabetic retinopathy (NPDR)

These patients show no other abnormalities in the picture below, but they do have at least one MA. Since results are frequently subtle, careful examination and observation are crucial. Every year, these patients ought to undergo a dilated eye exam. And there is a chance of five percent that mild NPDR will turn into PDR. A patient should be referred to a PCP for further examination if they are diagnosed with one or more MAs in their eyes and are suspected of being diagnosed with diabetes. You can keep an eye on patients' disease progression by recording tiny discoveries and specifying their precise locations. If available, use fundus images to facilitate comparisons in the future. Unless you have verified a diagnosis of DME or are concerned about a patient with mild NPDR, there is no need to refer them to a retina expert. Patients should be informed of the findings and their potential consequences, particularly if they are newly diagnosed with diabetes. It is crucial to explain to them that MAs signify early end organ damage from their condition. Motivate them to keep an eye on their nutrition and blood sugar levels. Provide the patient's PCP and/or endocrinologist a thorough report so they are aware of the results and can use it to help them decide on a course of treatment.

Stage 2: Moderate NPDR

Every six to eight months, patients with moderate NPDR should be examined. Within a year, there is a 12% to 27% chance that they will get proliferative diabetic retinopathy (PDR). In cases when you suspect DME, you may choose to obtain macular OCT images. Fundus photography is advised for these individuals. Unless you have proven DME or you feel OCT imaging is necessary but cannot obtain this technology, these individuals do not need to be referred to a retina expert. Informing these patients about the results and their implications for the course of the disease is crucial once more.

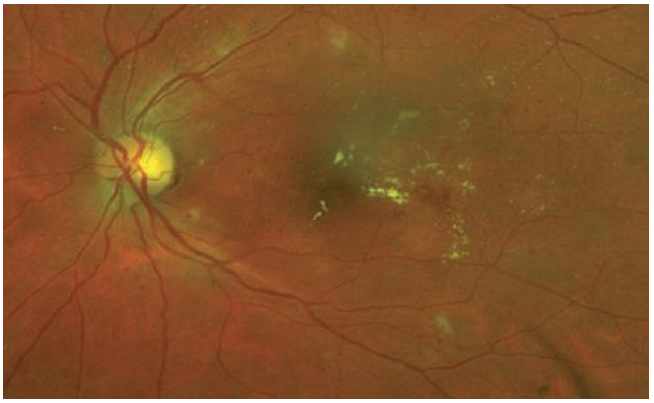

Figure 1 Patient with Moderate NPDR

It can be essential to send patients back to their PCP or endocrinologist earlier than planned so they can discuss treatment modifications, depending on their most recent blood sugar management and the results of their most recent diabetic examination with those professionals (Figure 1).

Stage 3: Severe NPDR

These patients exhibit venous beading in two or more quadrants, an IRMA in one or more quadrants, and intraretinal hemorrhages. The 4:2:1 rule refers to this. Neovascularization, which would suggest PDR, must not be present in these data.

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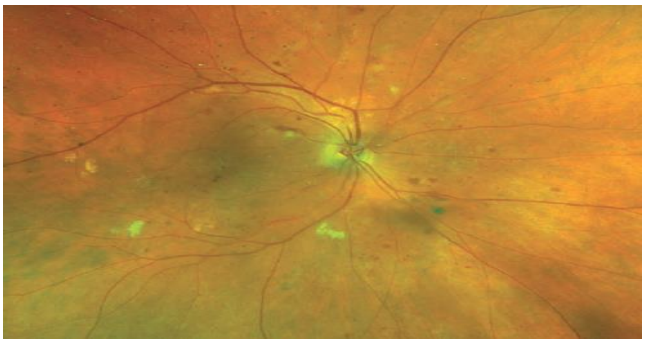

Figure 2 Severe NPDR

Macular OCT and fluorescein angiography should be used in conjunction to follow patients with severe NPDR to identify any early neovascularization or DME. Patients should be followed up with dilated fundus examinations every three to four months, and referrals to retina specialists are advised. To monitor these individuals, you might be able to collaborate with a retina specialist by scheduling alternating consultations. Discussing with patients who have severe NPDR the significance of blood sugar control and close observation is vital, since they have a 52% chance of developing PDR within a year. To discuss retinal findings, it is also necessary to contact the patient's PCP or endocrinologist. Currently, these patients are probably having neuropathy elsewhere and are at a significant risk of both permanent visual loss and disease progression (Figure 2).

Stage 4: Proliferative Diabetic Retinopathy

These patients show evidence of either vitreous/preretinal bleeding or neovascularization of the disc/elsewhere after their NPDR advanced to PDR. For additional testing and treatment, these patients need to be referred right away to a retina expert. Laser panretinal photocoagulation is the typical treatment for peripheral neovascularization. In addition, they frequently receive intravitreal injections of anti-VEGF, which may be administered in addition to PRP. These individuals require monthly follow-up visits with a retina specialist until their illness stabilizes. After that, they might see someone every six to twelve months. Inform the patient's PCP and/or endocrinologist of all results. If the patient's PDR is new, a phone call is necessary.

3. Research Methodology

One typical consequence of diabetes mellitus is diabetic retinopathy (DR), which results in retinal lesions that impair vision. It can result in blindness if it is not discovered early. Sadly, there is no cure for DR; therapy just keeps the eyesight intact. Early diagnosis and treatment of DR can greatly lower the risk of visual loss. Unlike computer-aided diagnostic techniques, the manual diagnosis procedure of DR retina fundus photographs by ophthalmologists is time-consuming, costly, and prone to misdiagnosis. Deep learning has emerged as one of the most popular methods recently, showing improved performance in several domains, including medical picture analysis and classification. Therefore, our goal was to create a deep learning-based DR detection method that would use deep learning both in the segmentation and detection stages. First, the conventional web data sources will be used to gather the necessary photos for the identification of DR. After that, the gathered picture will be sent for Swinunet-based blood vessel segmentation. To extract stacked features, for example, the segmented pictures will be fed into the Dilated-Densenet using Resnet. In order to provide promising outcomes over DR detection, the final stage detection will be performed with the assistance of Hierarchical Multi-scale RNN with parameter optimisation. The newly developed Manta Ray Foraging Optimization (MRFO) and Shark Smell Optimization (SSO) algorithm will be used here for maximizing the effectiveness of the developed DR detection approach. The implementation outcome will be analyzed over various DR detection approaches for validating the performance of the developed model.

4. Treatment for DME

From minor DR to severe proliferative disease, diabetic macular edema (DME) can develop at any stage of retinopathy. Over the previous twenty years, there has been a significant shift in the therapeutic paradigm for individuals with DME. The Early Treatment Diabetic Retinopathy Study (ETDRS) results, which showed that focal laser photocoagulation was superior to observation for clinically significant DME, although a significant proportion of treated patients eventually lost vision, served as the foundation for standard protocol for many years. Currently, intravitreal injections of one or more anti-VEGF medicines constitute the first-line treatment for the majority of DME cases. These drugs have good safety profiles and over time can stabilize

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and even improve vision. It is no longer a concern to determine whether DME meets the ETDRS criteria for clinical significance. Nowadays, doctors employ OCT to identify whether edema is center-involving or non-center-involving. Based on this finding and the patient's VA, they then decide what course of treatment to take. For imaging, identification, categorization, and management, OCT is unquestionably the gold standard of therapy, especially for patients whose BCVA is less than 20/20 and who do not have another evident cause of vision loss. Of course, we still perform OCT and view the macula stereoscopically through a dilated pupil.

Conclusion

Prior until recently, low vision rehabilitation and laser therapy were the only forms of treatment and management that doctors could provide to patients with DME and PDR. The future is now more promising than ever for people with diabetic eye disease thanks to the development of safe and efficient pharmaceutical treatments and the tremendously advancing of technologies like Artificial Intelligence, Machine Learning and Deep learning, that enhance both visual outcomes and quality of life.

Acknowledgements

The source of the study has been rooted to previous papers, Book chapters and FAAO.

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