International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 06 | June - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

Comparative Analysis of Diabetic Retinopathy Using Deep Learning Concepts

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Abstract: Diabetic retinopathy is a complication of diabetes that affects the eyes. It is a progressive disease that occurs in stages, each of which is characterized by specific changes in the retina. It is caused by damage to the blood vessels in the retina, which is the light-sensitive part of the eye that sends visual signals to the brain. People with diabetes, especially those with poorly controlled blood sugar levels, are at risk of developing diabetic retinopathy. Over time, high blood sugar levels can cause the blood vessels in the retina to become damaged or blocked. This can lead to swelling, bleeding, and the growth of abnormal blood vessels in the retina, which can cause vision loss or even blindness. Symptoms of diabetic retinopathy may include blurry vision, floaters (spots in the field of vision), and difficulty seeing at night. However, many people with diabetic retinopathy may not have any symptoms at all in the early stages of the condition. Treatment for diabetic retinopathy may involve controlling blood sugar levels, blood pressure, and cholesterol levels, as well as laser treatment, injections, or surgery in more advanced cases. Regular eye exams are also recommended for people with diabetes to detect any early signs of diabetic retinopathy and prevent vision loss.

Keywords: Diabetic Retinopathy; Deep Learning; Image processing; Convolution neural network

I. INTRODUCTION

Deep learning techniques have been used to develop algorithms for the detection and diagnosis of diabetic retinopathy from retinal images. These techniques use artificial neural networks that can learn from large datasets of retinal images to identify features that are indicative of diabetic retinopathy. One common deep-learning technique used for diabetic retinopathy is convolutional neural networks (CNNs). CNNs are designed to recognize patterns in visual data, such as images, and be highly effective in analyzing retinal images for diabetic retinopathy. In recent years, several studies have reported high accuracy rates for deep learning algorithms in detecting diabetic retinopathy from retinal images.

This paper presents a comparative analysis of various deep learning approaches for DR detection, evaluating their performance, robustness, and computational efficiency.

A comprehensive review of the literature reveals several deep learning architectures applied to DR detection, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their variants. These models leverage large-scale annotated datasets to learn discriminative features from fundus images, enabling accurate classification of DR severity levels and identification of associated lesions such as microaneurysms, hemorrhages, and exudates.

The comparative analysis encompasses evaluation metrics such as sensitivity, specificity, area under the receiver operating characteristic curve (AUC-ROC), and computational efficiency. Results demonstrate varying performance across different deep learning architectures, with some models exhibiting superior sensitivity and specificity in detecting DR-related lesions, while others prioritize computational efficiency and scalability for real-world deployment.

Furthermore, the study investigates the impact of dataset characteristics, including size, diversity, and annotation quality, on model performance and generalization capabilities. Strategies for data augmentation, transfer learning, and domain adaptation are explored to enhance model robustness and address challenges associated with limited labeled data and inter-dataset variability.

Finally, the paper discusses emerging trends and future directions in deep learning-based DR detection, including the integration of multimodal imaging modalities, such as optical coherence tomography (OCT) and wide-field fundus photography, and the development of explainable AI frameworks to elucidate model decisions and enhance clinical interpretability.

II. STAGES OF DR (DIABETIC RETINOPATHY)

Diabetic retinopathy (DR) progresses through several stages, each characterized by distinct clinical features and severity levels. The stages of diabetic retinopathy are broadly categorized into two main types: non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR). Here's a breakdown of these stages:

Non-Proliferative Diabetic Retinopathy (NPDR):

Mild NPDR: Characterized by the presence of microaneurysms, small areas of retinal hemorrhages, and retinal vascular abnormalities.

Moderate NPDR: In addition to the features of mild NPDR, there is an increased number and severity of hemorrhages and microaneurysms.

Severe NPDR: Characterized by extensive retinal hemorrhages, venous beading (irregular dilatation and constriction of retinal veins), intraretinal microvascular abnormalities (IRMA), and the presence of cotton wool spots (soft exudates).

Proliferative Diabetic Retinopathy (PDR):

Neovascularization: This stage is marked by the growth of abnormal new blood vessels (neovascularization) on the surface of the retina or optic nerve head. These vessels are fragile and prone to bleeding, leading to vitreous hemorrhage.

Fibrovascular proliferation: As the neovascularization progresses, fibrous tissue may proliferate, causing the formation of fibrovascular membranes. These membranes can contract and exert traction on the retina, leading to retinal detachment and vision loss.

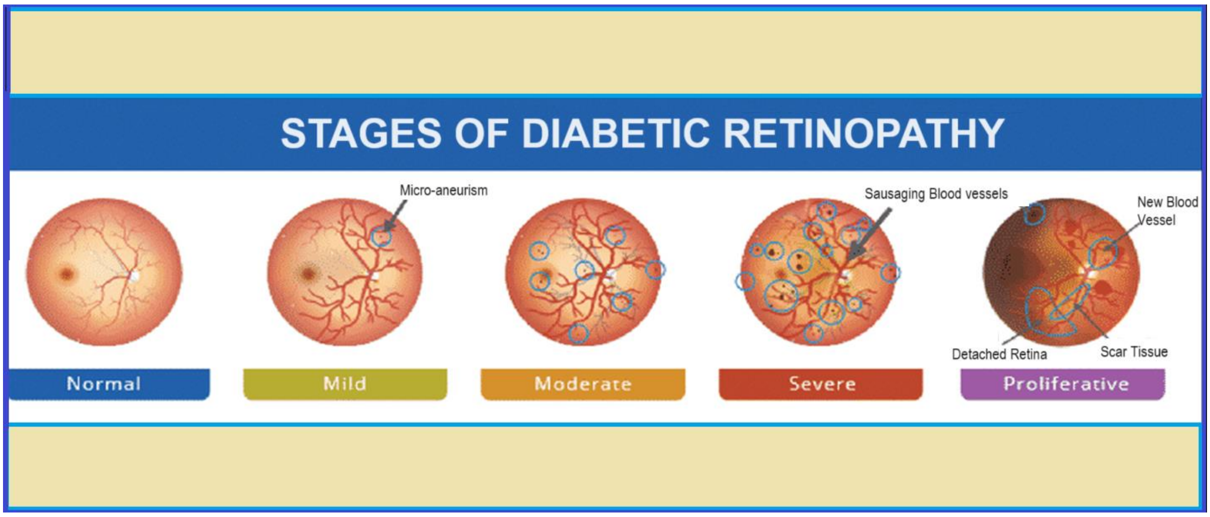

Figure 1: Stages of Diabetic Retinopathy

It's important to note that diabetic retinopathy can progress from mild NPDR to severe NPDR and eventually to PDR if left untreated. Early detection and management are critical for preventing vision loss and complications associated with advanced stages of DR. Regular eye examinations, optimal glycemic control, blood pressure management, and timely intervention with laser therapy, intravitreal injections, or surgery are essential components of DR management to preserve vision and prevent progression to advanced stages.

Here are some easy ways to identify diabetic retinopathy without any technique or tools.

Eye Exam: The most effective way to identify diabetic retinopathy is to have a comprehensive eye exam by an eye specialist or ophthalmologist. During this exam, our eye doctor will dilate our pupils and use a special instrument to examine the back of your eye, including the blood vessels in the retina.

Symptoms: Diabetic retinopathy may not show any symptoms in its early stages, but as it progresses, the patient may experience symptoms such as blurred vision, floaters, difficulty seeing at night, and changes in colour perception.

Regular Monitoring: If we have diabetes, it is important to have regular eye exams to monitor for diabetic retinopathy, even if we are not experiencing any symptoms. The American Diabetes Association (ADA) recommends annual eye examinations of diabetic patients, or more frequently if our doctor recommends it.

III. LITERATURE REVIEW

Diabetic retinopathy may not have any noticeable symptoms in the early stages, which is why regular eye examinations are recommended for people with diabetes. Early detection and treatment can help prevent or slow down the progression of diabetic retinopathy.

Deep learning techniques can be used to rectify each stage of diabetic retinopathy by training a neural network to classify the severity of the disease in retinal images.

In this paper Alghazo, J et al (2019) [2] three models of deep convolution neural network have been proposed for the classification of Diabetic Retinopathy. They used three channels Red, Green, and blue. Among the three, blue channels achieved the highest accuracy of 97.08 %. In this system initially, the input images are converted into grey-scale images and then given to the different channels.

In this method Chen, H et al (2019) [5] introduced a deep learning algorithm was proposed to employ a Siamese binary classification convolutional neural network for the early detection of diabetic retinopathy. Utilizing binocular fundus images as inputs, the model predicts the likelihood of diabetic retinopathy for each eye. Achieving an AUC of 0.951, with a sensitivity of 82.2% and specificity of 70.7%, this model demonstrates promising performance in early detection.

In this method, Chen, Y et al (2021) [11] used a convolutional layer and pooling layer in a convolutional neural network that applies a set of learnable filters to the input image. Convolutional layers are useful for learning spatial features in image pooling layers and reducing the spatial size of input feature maps by down sampling. Here max pooling and average pooling are used. As a result of using this filtering structure (convolution, max-pooling, average-pooling) the accuracy detected in the system is 92.0%, 93.2%, and 93.6%. ie Microneurism is mostly detected in the average pooling.

In this method, Embong, Z et al (2022) [12] proposed CNN based approach for neovascularization detection in retinal images. For this, popular convolution neural network architecture (CNN) such as AlexNet, Google Net, ResNet-18, and ResNet-50 are used. All these CNN Architecture are highly influential in the development of Deep Learning for Diabetic Detection. The system could achieve an accuracy of 91.57%, sensitivity of 85.69%, Specificity of 97.44%, and precision of 97.10%.

In this method, Zubair Khan et al (2021) [13] proposed VGG-NiN model offers the capability to process a DR image at any scale, facilitated by the SPP layer. Within this system, the stacked structure of NiN introduces non-linearity, contributing to improved classification. However, the system overlooked the incorporation of metaheuristic approaches for hyperparameter optimization, resulting in less competitive outcomes.

In this method, Harshit Kaushik et al (2021) [14] developed a stacked generalization model of CNN that surpassed state-of-the-art models in both binary and multi-class classification tasks. However, the system lacked the integration of metaheuristic approaches for hyperparameter optimization, leading to comparatively inferior outcomes.

In this method, Roc Reguant *et al.,* [15], Proposed was a CNN visualization scheme aimed at identifying the intrinsic image features utilized in the decision-making process of the CNN. Following this, an in-depth analysis was conducted on these features, focusing on well-established pathologies including haemorrhage, microaneurysms, exudates, and other ocular components.

IV. DATASETS

Several publicly available datasets have been used for the detection of diabetic retinopathy using deep learning.

Table 1 Comparison of Dataset

Ref	Data Set	Image Count	Size (px)	DR Grade	Camera Used
[4]	DRIVE	40	433*289 to 5184*3456	Yes	Digi fundus camera 45-degree field of view
[3]	Messidor	1200	3888*2951	Yes	Digi fundus camera of view 45-degree field
[1]	Eye PACS	100000	1024*1024 to 4896*3264		Digi Fundus camera
[8]	Kaggle	35000	256*256	Yes	Digi fundus camera
[14]	IDRiD	516	3*3mm scans	Yes	Topcon TRC-NW8 fundus camera with 45-degree field of view

The Diabetic Retinopathy Database (DRIVE) [9]: This dataset includes 40 color fundus images with corresponding annotations for the presence of diabetic retinopathy. The images were obtained using a digital fundus camera featuring a 45-degree field of view.

The Messidor dataset: This dataset includes 1,200 color fundus images with corresponding annotations for diabetic retinopathy severity. The images were obtained using a digital fundus camera featuring a 45-degree field of view.

The EyePACS dataset [10]: This dataset includes over 100,000 retinal images with corresponding annotations for diabetic retinopathy severity. The images were obtained using a variety of imaging methods, resulting in discrepancies in quality.

The Kaggle diabetic retinopathy dataset [8]: This dataset includes over 35,000 retinal images with corresponding annotations for diabetic retinopathy severity. The images were obtained using a variety of imaging methods, resulting in discrepancies in quality.

The Indian Diabetic Retinopathy Image Dataset (IDRiD) [14]: This dataset comprises 516 retinal images annotated for the severity of diabetic retinopathy. These images were obtained using a Topcon TRC-NW8 fundus camera equipped with a 45-degree field of view.

These datasets have been used to develop and evaluate deep-learning algorithms for the detection of diabetic retinopathy. However, it is important to note that there may be differences in image quality, disease severity, and other factors between these datasets, which could affect the performance of detection systems. Therefore, it is important to carefully evaluate the performance of deep learning algorithms using appropriate statistical methods and to validate their performance on additional datasets whenever possible.

V. PERFORMANCE MEASURES

Several performance measures can be used to evaluate the accuracy of diabetic retinopathy detection models. They are;

Sensitivity: This calculates the ratio of true positives (instances of accurately identifying diabetic retinopathy by the model) to all actual positive cases.

Specificity: This calculates the ratio of true negatives (cases without diabetic retinopathy correctly identified by the model) among all the actual negative cases.

Accuracy: This calculates the overall ratio of correct predictions made by the model, both true positives and true negatives, among all cases.

Precision: This calculates the true ratio of positive cases among all the cases predicted as positive by the model.

Recall: This evaluates the true ratio of positive cases identified by the model among all actual positive cases.

F1 score: The Model's accuracy in binary classification can be measured through the F1 score, tasks that take into account both precision and recall.

Area under the Receiver Operating Characteristic Curve (AUC-ROC): This evaluates the model's capacity to differentiate between positive and negative cases, which is especially valuable in datasets with imbalanced proportions of positive and negative instances.

Table 2. Performance comparison of review papers

Paper Ref	Accuracy	Sensitivity	Specificity	Precision	F1 score	AUC	Method used
1	87.83	77.81	93.8	-	-	0.93	Bichannel convolution Neural network
3	0.82	0.84	0.80	-	-	0.84	Optical coherence Tomography Angiography images using ML
6	0.956	0.956	0.989	0.956	-		GENet based on GCA attention mechanism
7	85	55.6	91	67	59.6	-	VGG-NiN model
12	80.83	-	86.7	-	-		Deep Learning ensemble approach
15	.94	.948	.936	-	-	-	Deep Convolution Neural Network
10	98.5	100	97.3	-	-		Multifractal + Support Vector Machine
13	97.92	0.96	-	1.00	0.96		Stacked Generalization of CNN
17	0.924	.931	.905	-	-	-	CANet
18	0.891	.900	.837	-	-	-	ANFIS

VI. METHODS FOR THE DETECTION OF DIABETIC RETINOPATHY

Various methods are employed for the detection of diabetic retinopathy (DR), ranging from traditional clinical examinations to advanced imaging technologies and artificial intelligence (AI) applications. Here are some common methods used for DR detection:

Fundus photography:

Color Fundus Photography: Traditional fundus photography involves capturing detailed color images of the retina. Eye care professionals examine these images for signs of diabetic retinopathy, such as microaneurysms, hemorrhages, and exudates.

Wide-Field Fundus Imaging: Provides a broader view of the retina, facilitating the detection of peripheral lesions. It is particularly useful for identifying early signs of diabetic retinopathy.

Optical coherence tomography (OCT) [1][6]:

OCT Imaging: This is a non-invasive imaging technique that uses light waves to capture high-resolution images of the retina. OCT findings influence treatment decisions in diabetic retinopathy. For example, if OCT reveals significant macular edema (swelling in the central part of the retina), treatment with anti-vascular endothelial growth factor (anti-VEGF) injections or laser therapy may be recommended to reduce the edema and preserve vision. OCT-guided treatment helps optimize outcomes and minimize the risk of vision loss.

Fluorescein Angiography (FA):

FA Imaging: Involves the intravenous injection of fluorescein dye, which highlights blood vessels in the retina. It is useful for assessing retinal blood flow, identifying areas of leakage, and detecting neovascularization.

Automated Screening Programs:

Automated Image Analysis: Computer algorithms analyze fundus images to detect and grade diabetic retinopathy lesions automatically. These systems may use machine learning and deep learning techniques for classification.

Telemedicine Screening: Remote assessment of fundus images by trained graders or automated systems, allowing for efficient screening of a large number of patients, especially in areas with limited access to eye care.

Artificial Intelligence (AI) Approaches:

Deep Learning Models: Convolutional Neural Networks (CNNs) and other deep learning architectures are trained on large datasets to automatically identify features of diabetic retinopathy in fundus images.

Machine Learning Algorithms: Traditional machine learning algorithms may be employed for feature extraction and classification of diabetic retinopathy based on various image characteristics.

Telemedicine screening: This involves using digital retinal imaging and telemedicine technology to remotely screen patients for diabetic retinopathy. Patients can have their retinal images captured at a primary care facility and sent to a specialist for analysis, allowing for early detection and treatment.

Point-of-Care Devices:

Handheld Fundus Cameras: Portable devices that can capture fundus images at the point of care, enabling screening in primary care settings or remote locations.

Smartphone-Based Imaging: Utilizing smartphone cameras and attachments for retinal imaging, enabling cost-effective and accessible screening.

Clinical Examination:

Dilated Eye Examinations: Standard clinical examinations by ophthalmologists or optometrists involving the use of dilated pupils to visualize the retina and assess for signs of diabetic retinopathy.

The choice of method often depends on factors such as the level of expertise available, the resources in a particular healthcare setting, and the stage of diabetic retinopathy being targeted. Integrating multiple methods and leveraging advancements in imaging technologies and artificial intelligence can enhance the accuracy and efficiency of diabetic retinopathy detection.

Early detection of diabetic retinopathy is important for preventing vision loss and other complications associated with the disease. The choice of method for early detection may depend on factors such as the severity of the disease, the availability of resources, and the preferences of the healthcare provider and patient.

The choice of performance measure depends on the specific requirements and goals of the diabetic retinopathy detection task and may vary depending on factors such as the severity of the condition, the size and complexity of the dataset, and the intended use of the model.

Several deep learning methods have been used for the early detection of diabetic retinopathy (DR), including convolutional neural networks (CNNs), deep belief networks (DBNs), and recurrent neural networks (RNNs).

Among these, CNNs have been shown to be particularly effective for the early detection of DR [7]. CNNs are a type of neural network that can automatically learn and extract features from images, making them well-suited for analysinga retinal images and detecting subtle changes that may indicate the presence of DR.

In recent years, several studies have demonstrated the effectiveness of CNN-based models for the early detection of DR. For example, the DeepDR model, which is based on a deep CNN, achieved an area under the curve (AUC) of 0.95 on a dataset of retinal images, outperforming other state-of-the-art methods for DR detection. Similarly, the IDRiD (Indian Diabetic Retinopathy Image Dataset) challenge, which was held to evaluate DR detection models, showed that CNN-based models outperformed other machine learning methods.

The popularity of CNN-based models for DR detection can be attributed to their ability to learn and extract complex features from retinal images, which enables them to detect subtle changes that may be missed by other methods. Additionally, CNN-based models can be trained on large datasets of retinal images, allowing for robust and accurate detection of DR.

VII. CONCLUSION

From the above factors, it is reasonable to conclude that deep learning has the potential to be a valuable tool in the detection of diabetic retinopathy. However, it is important to note that deep learning algorithms are not perfect and may produce false positives or false negatives. Therefore, these algorithms should always be used in conjunction with clinical expertise and other diagnostic tools to ensure accurate diagnoses.

In summary, CNN-based models are currently the most commonly used and effective deep learning method for the early detection of DR. The effectiveness of these models may vary depending on the specific dataset and the quality of the retinal images used for analysis. Therefore, careful evaluation and validation of these models are necessary before their implementation in clinical practice. Based on the Literature review in all cases, the neural network can be trained using a large dataset of retinal images that have been annotated by experts to indicate the severity of diabetic retinopathy. The trained neural network can then be used to automatically classify new retinal images and provide an assessment of the severity of the disease. This can help to improve the accuracy and efficiency of screening and diagnosis for diabetic retinopathy.

DECLARATION OF COMPETING INTEREST

The authors declare that the information presented is as objective and unbiased as follows. Referenced papers that appeared in this paper are for only my review purpose of the research.

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