International journal of basic and applied research
www.pragatipublication.com
ISSN 2249-3352 (P) 2278-0505 (E)
Cosmos Impact Factor-5.86

Retina Care AI: Deep Learning-Based Diabetic Retinopathy Detection System

[1]Sunkoju Gayatri, [2]V. Nikitha,
[1]M.Tech Scholar,Dept. of CSE , Malla Reddy Technical Campus,Malla Reddy Vishwavidyapeeth, Maisammaguda,Hyderabad, Telangana 500100, India, thaligarigayatri@gmail.com
[2]Assistant Professor, Dept. of CSE, Malla Reddy Technical Campus, Malla Reddy Vishwavidyapeeth, Maisammaguda, Hyderabad, Telangana 500100, India, nikithaveeramalla@gmail.com

ABSTRACT:

People with diabetes are more likely to develop diabetic retinopathy (DR), which is a leading cause of blindness and visual loss worldwide. Correct staging of DR and prompt diagnosis are crucial for effective treatment and the avoidance of vision loss. One typical and arduous method for diagnosing and classifying DR phases is manually inspecting retinal images. However, this approach is also quite error-prone. This research introduces a novel approach to diabetic retinopathy stage classification using NNs, a popular deep learning model for sequential data. We feed preprocessed retinal photos to a NN model that has been trained to classify diabetic retinopathy (DR) into its various phases, starting with no retinopathy and ending with proliferative DR. We extract essential properties from these photographs. The model is able to effectively manage changes in retinal features over time by learning temporal correlations from sequential image input. The experimental results demonstrate that the NN model consistently and correctly categorizes DR phases, in comparison to more traditional techniques. Improved management of diabetic eye disease and earlier treatment of the condition may result from this approach assisting ophthalmologists in making more precise diagnosis of DR.
Keywords:Diabetic Retinopathy, Deep Learning, Convolutional Neural Network, Transformer, Diagnosis.

Introduction

A common and serious complication of diabetes mellitus, diabetic retinopathy (DR) destroys the blood vessels in the retina and may lead to visual impairment or even blindness if left untreated. As the number of people diagnosed with diabetes continues to rise globally, diabetic retinopathy has become a major concern for public health. Mild non-proliferative retinopathy (NPDR) is the initial stage of diabetic retinopathy, which typically progresses to more severe phases like proliferative diabetic retinopathy (PDR). Early detection and accurate classification of DR are crucial for disease prevention and the provision of appropriate medical intervention. Accurate DR staging is critical for deciding on the most effective treatment plan to prevent irreversible vision loss. However, the most reliable method for diagnosing and classifying DRs is still ophthalmologists manually examining retinal scans. Due to its labor-intensive nature, lengthy processing time, and reliance on the clinician's proficiency, this procedure carries the risk of inconsistent results and diagnostic delays.There has been a significant uptick in research into medical image analysis using deep learning and machine learning techniques to address these issues. Even though Convolutional Neural Networks (CNNs) have shown promise for retinal image classification, these methods often miss sequential or temporal alterations in the disease's progression. On the other hand, there exist Recurrent Neural Networks (RNNs) that offer impressive potential in areas like artificial intelligence (AI) and natural language processing (NLP) due to their ability to process sequential input. Their ability to discern temporal correlations in image sequences makes them well-suited for classifying phases of diabetic retinopathy, which occurs when changes occur in the retina over time.This study explores the use of RNNs for the categorization of diabetic retinopathy stages. Using the temporal features of retinal picture sequences, we want to provide a more effective technique of DR classification that could help with the diagnosis and treatment of the disease. To reduce the risk of diabetic retinopathy-related blindness, the proposed method offers a possible means to improve early detection and enable rapid intervention.

Arteriolar narrowing detection, computer-assisted laser surgery, hypertensive retinopathy characterization, screening programs for diabetic retinopathy, and evaluation of retinopathy of prematurity are some of the many uses for retinal vessel segmentation. Among the many indirect applications are the following: determining the precise location of the optic disc and fovea; automatically developing retinal maps for the treatment of age-related macular degeneration; synthesising mosaics of retinal images; and extracting characteristic points of the retinal vasculature for use in temporal or multimodal image registration. Despite a lack of comprehensive research, biometric identification might one day make use of the retinal vascular network since it is distinct from one individual to another. Retinal picture registration, illumination correction, and illness detection are just a few of the many uses for the human retina's three most important components: the vasculature, the fovea, and the optical disk. Determining the presence of these critical structures manually requires substantial user expertise and time. There are a number of reasons why it could be difficult to separate blood vessels from fundus pictures. Retinal images have their own unique properties, and there are other aspects related to the imaging technique and the gathering procedure that might introduce artifacts into the final product. The two most critical factors that make segmentation difficult are uneven illumination in the background and inadequate contrast between the retina and the image. The improper contrast and distorted lighting are both caused by the acquisition process and the fact that different boats stand out against the background in different ways. To put it another way, arteries may be easier to notice than veins. When comparing thick vessels to other kinds of vessels, the background stands out more. In addition, there are other factors that must be considered, such as background noise, the optical disk and fovea, different sized arteries, lesion effects, etc. So, it would be great if there was an automated device that could swiftly and properly segment the blood vessels in the retina.
A number of methods have been developed and put into practice with the aim of segmenting retinal images. We may classify algorithms in this field into three broad types: tracking-based, window-based, and classifier-based. Edge detection and other window-based techniques estimate a model match at each pixel by using the surrounding window. Rotating matching filters were used for detection after a Gaussian-shaped curve was employed to mimic the retinal image's vascular cross-section. There are two stages to the process that classifier-based methods follow. At the base level, an algorithm is used to create a segmentation of regions that are geographically connected. Thereafter, these prospective spots are classified as vessel or non-vessel. Using a profile model, tracking-based methods gradually divide a vessel. Before tracking can start, a collection of initial points is needed. There are two typical approaches to selecting the seed points: one is labor-intensive and depends on the user's prior knowledge, while the other is automated. The tracking is most rigorous at the seed level, and ridges may be found by checking to see whether the curvature and gradients intersect at zero. Any vessel segments that do not fit the given parameters will not be included in the subsequent analysis. These segments might be too tall (greater than 30 pixels) or too wide (more than 100 pixels). This study suggests a method based on curvelet transform to enhance vascular detection in retinal pictures. Debutted the curvelet transform, a new multiscale transform, in the last decade. The anisotropy scaling rule and directionality are two essential features of a geometrical transition called a curvelet. Because of its superiority in sparse representation and management of image singularities, curvelet stands out among other multiscale transformations.

Literature Survey

Many improved CNN-based DR detection models have been created, each addressing different aspects, thanks to recent advancements in deep learning. distinct challenges associated with evaluating fundus pictures. In order to improve the accuracy, efficiency, and resilience of DR diagnosis, these models use many methodologies. A novel approach to diabetic retinopathy (DR) detection that employs deep learning techniques. An important aspect of early diagnosis, this method aims to automate DR recognition and grading. According to Romero-Oraa et al. (2024), the model might include an attention mechanism to focus on certain aspects of the retinal images.

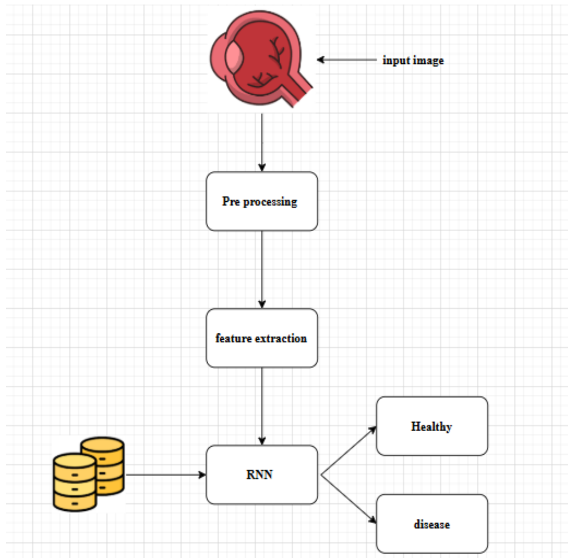
Specifically, it demarcates between light-colored buildings and dark-colored ones. The higher classification accuracy is a result of the model's enhanced ability to distinguish between the many DR-related traits and patterns. The framework further deconstructs the provided images. This dissection is being done so the lesions may be seen more clearly in the pictures. In addition, it generates understandable attention maps. The model's predictions and the logic behind them may be better understood by doctors by looking at these maps. Verified on the Kaggle DR Detection dataset, the model's accuracy stands at 83.7% and 0.78 on the quadratic weighted Kappa. These results are significant since they outperform many current best practices. Doctors may use the framework as a diagnostic tool to aid with DR grading and early detection due to its valuable properties. The bilayered neural network is one of the well-known methods for DR detection. It employs a two-layer feedforward architecture, as stated by Islam (2021). It could be challenging to take images of the retina due to differences in illumination and people's field of vision. Because of these features, DR may be harder to diagnose. The goal of the two-pronged approach is to solve these problems. Because of this, the model is able to gather and categorize information better, which allows it to recognize changes in DR severity with more subtlety.The model's unique design allows it to comprehend complex patterns seen in fundus images. Proof of this is its 93.33% performance on the test set. Adding resubstitution validation greatly optimizes its performance. Thus, it shows promise as a method for automated DR detection in healthcare settings.

Low-quality fundus photos are sometimes used in DR diagnosis (Nneji, 2022). Both the CLAHE (contrast-limited adaptive histogram equalization) and the CECED (contrast-enhanced canny edge detection) scans, which consist of two channels, are processed by the network. This technique allows it to handle the intricacy of low-quality photographs better. Features are extracted by WFDLN utilizing Inception V3 and VGG-16 that have been fine-tuned. Together, they produce remarkable results. With an accuracy of 98.5%, a sensitivity of 98.9%, and a specificity of 98.0%, it performed well on the Messidor dataset. These results demonstrate its efficacy in automated DR classification, and its high accuracy and resilience allow it to solve common problems in fundus image processing. Not only that, but the likelihood of developing referable DR may be predicted using a model trained on 156,363 fundus photos from the EyePACS collection (Bora, 2021). One significant enhancement is the model's ability to predict the probability of producing referable DR. Combining scores from many images yields an area under the curve (AUC) of 0.81. This paves the way for the development of individualised risk assessments, which may lead to better screening procedures and faster responses.

When it comes to deep learning models for medical image segmentation, the BigAug approach is revolutionary, says Zhang (2022). This method employs ad hoc adjustments to strengthen the models against variations in medical imaging data. Due to the potential for substantial variation in medical imaging data, this approach is crucial. The BigAug method produces results that are on par with those of fully supervised models. By expanding the applicability of deep learning techniques in a variety of clinical settings, this groundbreaking innovation enhances the precision and efficiency of diagnostic procedures, particularly in the area of autonomously processing fundus photos for diabetic retinopathy grading.

Methodology

A Recurrent Neural Network (RNN) is proposed as a means of classifying retinal images into distinct diabetic retinopathy (DR) stages. In contrast to spatial patterns based only on images, Real-Natural Neural Networks (RNNs) perform better when presented with sequential or time-based data. By analyzing the changes in retinal features as DR advances, RNNs make it feasible to monitor the disease's progression. Using RNNs, this method addresses the shortcomings of previous approaches to diabetic retinopathy and its complex progression. If implemented, this method has the potential to significantly enhance the precision and consistency of DR stage forecasts. In addition to tracking changes over time, it may also gather static data from individual retinal photographs.



System architecture

Labeling retinal fundus photos as "healthy," "mild," "moderate," "severe," or "proliferative" is a typical approach that helps with the initial step of data collecting for the proposed system. Medical photo archives like as EyePACS, Kaggle, or other specialized DR collections were used to gather these images. All of the photographs in the collection depict either a normal retina or a specific stage of diabetic retinopathy. It would be helpful to label the photos with the DR stage or with information about a healthy retina. Ensuring that the training data accurately represents all phases is a crucial step in training the model. Preprocessing: Resizing and Converting BGR to RGB: After gathering a dataset, the images are preprocessed to get them suitable for analysis. Images are reduced to a consistent resolution, say 224x224 pixels, to standardize the input size. This is necessary for both deep learning models, such as CNNs, and traditional machine learning models, like SVM. Additionally, the images are converted from their native BGR format—used by OpenCV—back to their native RGB format—used by deep learning frameworks. The correct understanding of the color values by the machine learning models relies on this conversion. Image quality may be enhanced by the application of additional preprocessing procedures including normalization, contrast correction, and noise reduction.

Data Visualization:

Data visualization is a powerful tool for comprehending dataset features and identifying issues like class imbalance or discrepancies in image quality. Visualization tools such as Matplotlib or Seaborn are used to generate distribution graphs, pie charts, and histograms that illustrate the occurrence of each DR stage within the dataset. To check whether the dataset is balanced, you may look at the distribution of images throughout the different stages, such as healthy, mild, moderate, severe, and proliferative. Additionally, you may see sample images from each stage to assess the data's diversity and quality. Accurate visualization is crucial for figuring out whether the dataset is fit for model training and if preprocessing is required.

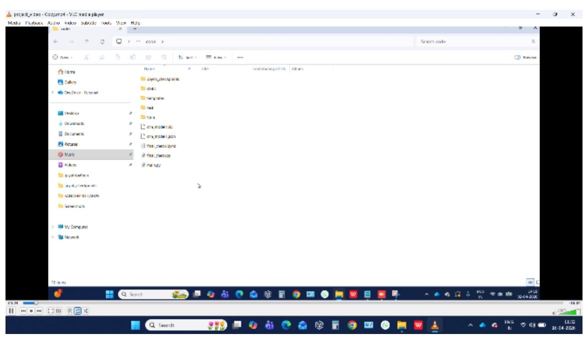
Separating Data Sets:

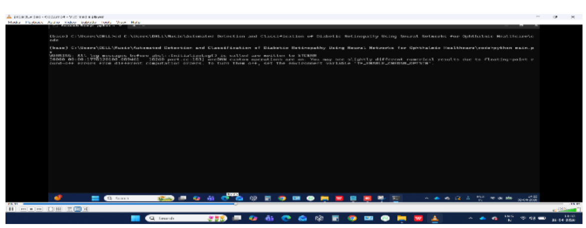
After visualizing and preprocessing the dataset, it is divided into three parts: training, validation, and test. Thanks to this split, the model can be trained on part of the data and its performance can be assessed on unknown data. Typically, a ratio of 80/20 or 70/30 is used, where 80% of the data is used for training and 20% is used for testing. It is usual practice to use a validation set that represents 10-15% of the data during training to prevent overfitting and fine-tune hyperparameters. To find out whether the model can handle unseen photographs, we need to utilize the data splitting step to test it on distinct data.

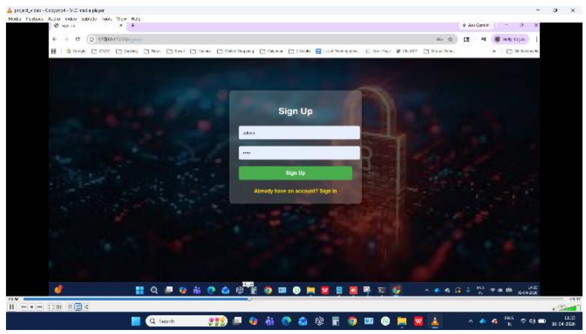
Gradient Boosting Algorithm (GBA):

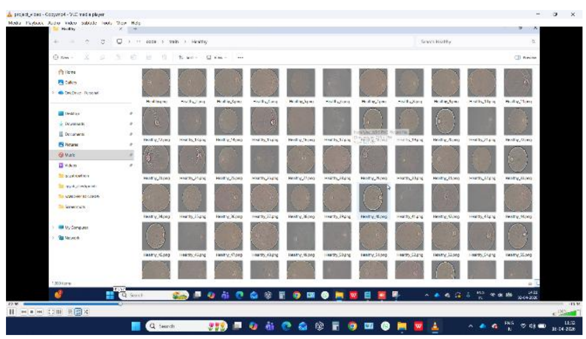
When it comes to machine learning techniques for classification and regression, the Gradient Boosting Algorithm (GBA) is among the best. As a subset of ensemble learning, it merges many less robust models (often decision trees) into a more robust prediction model. Trains new models sequentially to address the defects using earlier models' errors as a starting point. The ensemble's residual errors, or the difference between the expected and actual values, are projected by each new model as part of gradient boosting. Thanks to its use of the gradient descent approach to reduce error, this technique is appropriately called "gradient boosting." The final prediction is the product of integrating the outputs of all the previous models and assigning a weight to each one based on its performance.

Results









Importing more input photographs for classification is the last step after training the models. These input photographs are first preprocessed by resizing and color converting them before they are fed into the trained models. By analyzing the input image, the GB and RCNN classifiers will forecast the retina's condition and, if affected, the degree of the illness (e.g., mild, moderate, severe, or proliferative). A label or likelihood score may be shown for each DR step's outcome. The system's effectiveness is evaluated by its ability to identify and classify unseen input photos for the presence and severity of diabetic retinopathy.

Conclusion

The proposed method employs cutting-edge machine learning algorithms, namely RNNs and RCNNs, to identify and categorize diabetic retinopathy (DR) from retinal fundus images. By combining these models, the approach may more accurately classify DRs, which speeds up the process of identifying DR stages and detecting critical features like microaneurysms and hemorrhages. Traditional approaches, such as Gradient Boosting Algorithms (GBA), have challenges such as computational complexity and the difficulty of handling sequential data. This hybrid approach partly resolves these concerns. In order to improve feature extraction and classification, the model uses RNNs for processing temporal data and RCNNs for accurately focusing on critical retinal regions. This allows it to follow the evolution of DR over time. The results demonstrate the potential of deep learning models for automated DR detection, which may aid in early diagnosis and treatment, hence decreasing the risk of diabetes blindness.

Future Scope

Several potential avenues exist for future improvements to DR classification. One option is to look at multi-modal techniques, which combine many forms of data to improve classification accuracy. This comprises information on the patient's demographics, health background, and image data. Second, the system's performance on smaller-scale or domain-specific datasets might be improved by using large-scale pre-trained models. Another promising development is the use of ensemble techniques, which combine the capabilities of several models to construct systems with even higher resilience. Classifiers such as Gradient Boosting and DNNs fall under this category. In addition, DR screening might be more accessible in underprivileged or rural regions if real-time DR categorization could be done using cloud-based systems or mobile devices, allowing for on-the-go diagnosis. Lastly, there is a need to improve the interpretability of machine learning models. Methods like explainable AI may provide light on the reasoning behind the model's predictions, enhancing its reliability for clinical applications.

References

[1]. [1]. Haq NU, Waheed T, Ishaq K, et al. Computationally efficient deep learning models for diabetic retinopathy detection: a systematic review. *Artif Intell Rev*. 2024.
[2]. Mutawa AM, Al-Sabti K, Raizada S, et al. A deep learning model for detecting diabetic retinopathy stages. *Appl Sci*. 2024.
[3]. Youldash M, Rahman A, Alsayed M, et al. Early detection and classification of diabetic retinopathy using deep learning. *AI*. 2024.
[4]. Wang TW, Luo WT, Tu YK, et al. Deep learning systems for fundus diabetic retinopathy detection: systematic review. *npj Digit Med*. 2025.
[5]. Hemanth SV, Alagarsamy S, Rajkumar TD. CNN-based model for diabetic retinopathy detection. *J Biomol Struct Dyn*. 2025.
[6]. Abu-Shawish I, Sudipta M, Abdel-Raheem E, et al. Deep learning in diabetic retinopathy detection: survey. *IEEE Access*. 2024.
[7]. Sebastian A, Elharrouss O. Deep-learning-based diabetic retinopathy classification survey. *Diagnostics*. 2023.
[8]. Gong W, Pu Y, Ning T, et al. Deep learning for enhanced prediction of diabetic retinopathy. *Front Med*. 2025.
[9]. Al-Kamachy I, Hassanpour R. Classification of diabetic retinopathy using pre-trained models. *arXiv*. 2024.
[10]. Shah E, Patel J. Diagnosis of diabetic retinopathy using ML and DL techniques. *arXiv*. 2024.
[11]. Uppina A, Krishnan SN. CNN-based UNET models for diabetic retinopathy detection. *arXiv*. 2024.
[12]. Majumder S, Kehtarnavaz N. Multitask deep learning model for DR detection. *IEEE*. 2021.
[13]. Gulshan V, et al. Development and validation of deep learning algorithm for DR detection. *Nat Med*. 2020.
[14]. Ting DSW, et al. AI for diabetic retinopathy screening. *Lancet Digit Health*. 2020.
[15]. Li Z, et al. Deep learning for detecting retinal diseases. *Ophthalmology*. 2021.
[16]. Quellec G, et al. Deep image mining for diabetic retinopathy screening. *Med Image Anal*. 2021.
[17]. Voets M, et al. Replicating deep learning models for DR detection. *NPJ Digit Med*. 2020.
[18]. Pratt H, et al. CNN-based DR detection using Kaggle dataset. *Procedia Comput Sci*. 2021.
[19]. Abràmoff MD, et al. Automated DR detection using AI. *IEEE Trans Med Imaging*. 2021.
[20]. Krause J, et al. Grader variability and DL systems in DR detection. *Ophthalmology*. 2021.