Engineering and Scientific International Journal (ESIJ)
Volume 11, Issue 1, January – March 2024

ISSN 2394-7187(Online)
ISSN 2394 - 7179 (Print)

Diabetic Retinopathy Classification through Convolutional Neural Network

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Abstract — An innovative approach to diabetic retinopathy classification utilizing convolutional neural networks (CNNs) is presented in this research. Diabetic retinopathy, a severe complication of diabetes and a leading cause of blindness worldwide, necessitates accurate and timely diagnosis for effective treatment and management. A deep learning framework based on ResNet-18 architecture is developed to automatically classify retinal images into different stages of diabetic retinopathy. The proposed model demonstrates noteworthy accuracy and efficiency. Experimental results on a large dataset validate the effectiveness of the approach, offering potential applications in clinical practice for early detection and intervention of diabetic retinopathy. The findings of this research offer significant implications for enhancing healthcare outcomes in ophthalmology through the integration of artificial intelligence.

Keywords: *Diabetic Retinopathy; Image Classification; Convolutional Neural Network; Resnet 18*.

1. Introduction

Diabetic retinopathy (DR) is a consequential complication of diabetes mellitus, posing a significant threat to vision if left unaddressed. Its prevalence has surged alongside the global rise in diabetes cases, particularly notable in regions like Asia. DR affects approximately one-third of individuals diagnosed with diabetes, with an estimated 420 million people worldwide grappling with the condition. Classified into five stages based on the Study of the Early Treatment Diabetic Retinopathy, this chronic eye ailment progresses from the initial Normal stage to Mild, Moderate, Severe Non-Proliferative Diabetic Retinopathy (NPDR), culminating in Proliferative Diabetic Retinopathy (PDR). Each stage delineates varying degrees of retinal blood vessel damage, ranging from microaneurysms and hemorrhages to the growth of abnormal vessels, potentially leading to severe vision impairment and blindness. Early detection through regular eye examinations is paramount for instituting timely interventions, such as laser therapy or surgery, to forestall further vision loss and uphold visual function, underscoring the imperative for proactive management

amidst the escalating prevalence of diabetes world wide.Detecting and treating visual loss early is the key to preventing visual loss . In severe cases, the vessels swell, leak fluid, or block blood vessels, which results in abnormal blood vessel growth and complete blindness. Microaneurysms, hemorrhages, and exudates are the main symptoms of DR on the retina. A lesion’s shape, size, and overall appearance determine its severity. Fundus photography is an ophthalmologic screening method for DR . Preventing diabetes-related blindness is clinically effective and cost-effective with an automated assessment technique .

The below figure shows the Stages of diabetic retinopathy (DR) with increasing severity.

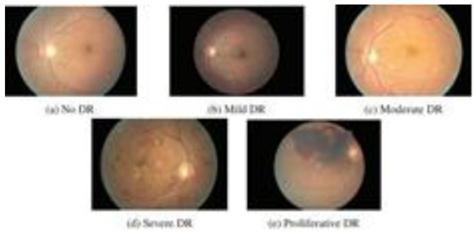

Fig.1: Stages of diabetic retinopathy

2. Background Study

Extensive research has explored binary and multi-class classification of diabetic retinopathy (DR), yielding promising outcomes. Gardner et al. achieved 88.4% sensitivity and 83.5% specificity using Neural Networks and pixel intensity values on a dataset of around 200 images. Nayak et al. extended this to three-class classification, obtaining 93% accuracy on 140 images by incorporating features such as the area of exudates and blood vessels. For five-class classification, Acharya et al. reported an average accuracy of 82% using support vector machines (SVMs) with higher-order spectra features. They also achieved 85.9% accuracy by calculating the areas of crucial features like blood vessels using image processing techniques. Adarsh et al. utilized image processing for automated diagnosis, reaching accuracies of 96% and 94.6% on public databases DIARETDB0 and DIARETDB1 respectively. However, the methods rely on feature extraction and have only been validated on small datasets, indicating limited real-time applicability compared to convolutional neural networks (CNNs). The motivation for pursuing diabetic

DOI: **10.30726/esij/v11.i1.2024.111003**

retinopathy (DR) classification with Convolutional Neural Networks (CNNs) is driven by the need to leverage deep learning capabilities for accurate and efficient analysis of large retinal imaging datasets.

3. Proposed Methodology

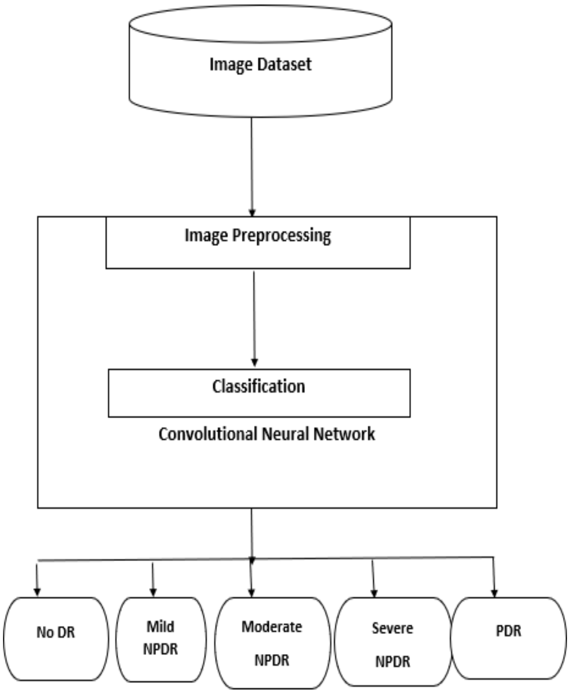

Fig.2: The above figure shows the process flow of the diabetic retinopathy classification.

3.1 CNN Architecture

A CNN is a Deep Learning technique that can take an input image, assign various objects and elements values (learnable weights and biases), and differentiate between them. Comparatively, preprocessing time for a CNN is much lower than for other classification methods. Unlike simple techniques where filters are hand engineered, CNN can learn these filters and their attributes. The structure of the visual cortex served as inspiration for the construction of a CNN, which resembles the human brain's interconnected network of neurons. Individual neurons can only respond to stimuli in the restricted region of the visual field known as the Receptive Field. There are numerous overlapping areas like this that fill the full visual field.

3.2 Data Collection

The dataset utilized in this investigation encompasses a diverse array of images sourced from multiple outlets, encompassing online repositories. It consists of 3662 images distributed across five classes portraying both healthy retinas and retinas afflicted by different stages of diabetic retinopathy.The first stage of setting up a Convolutional Neural Network (CNN) model starts with importing necessary libraries.

3.3 Image Preprocessing

Pre-processing is a crucial stage in preparing the dataset for training the convolutional neural network (CNN) model. The images in the considered dataset were collected from rural parts of India under diverse conditions, leading to a lack of uniformity among them. Utilizing these images in their raw form would not have yielded the desired results. Therefore, preprocessing was necessary to enhance the images before feeding them into the neural network model. The application of various preprocessing techniques aimed to standardize and optimize the images, ensuring improved quality and facilitating accurate analysis and classification. The size of the images in the dataset was not uniform, as they were collected from different places.

3.4 Model Development

The dataset is splitted into two parts: the training set and the test set. The training set, consisting of (80%) of the data, is used to train the deep learning models, while the test set (20%) is reserved for the model evaluation. The convolutional neural network (CNN) model was trained using the provided dataset, encompassing images representative of diabetic retinopathy conditions. Training involved iterating through epochs with a specified batch size, employing the stochastic gradient descent (SGD) optimizer to update model parameters. Throughout the training process, the model's performance was closely monitored on a validation dataset to mitigate the risk of overfitting and ensure generalization capability.

3.5 Model Evaluation

Upon completion of training, the CNN underwent testing to gauge its efficacy in classifying diabetic retinopathy severity. Metrics from this evaluation affirm the model's performance and its potential for practical use in diagnosing and managing the condition. This validation ensures the model meets required standards for real-world healthcare applications. Following the evaluation of the trained Convolutional Neural Network (CNN) model, the subsequent step involves showcasing its practical utility in diagnosing diabetic retinopathy.For this purpose, a web application has been developed leveraging Flask, a micro web framework for Python. This interactive platform allows users to upload the retinal images, which are then processed by the trained model for disease classification. Upon submission, the model predicts the severity of diabetic retinopathy based on the uploaded image and provides the corresponding classification label. Through this intuitive web interface, users can swiftly and effectively diagnose diabetic retinopathy, thereby demonstrating the real-world applicability of the trained model.

4. Experimentation and Result

During the experimentation phase, a ResNet-18 based convolutional neural network (CNN) was trained using a diverse dataset of retinal images spanning various stages of diabetic retinopathy. And The outcomes of this project are remarkable, with an impressive 82% accuracy achieved in DR classification. Prior to training, the dataset underwent preprocessing to ensure consistency and optimize the model's performance. Throughout the training process, which encompassed multiple epochs, the model assimilated intricate patterns and features associated with different diabetic retinopathy stages. Techniques such as data augmentation and transfer learning were employed to bolster the model's robustness and generalization capabilities. Subsequently, the trained model underwent evaluation on a distinct validation dataset to gauge its performance across key metrics including accuracy, precision, recall, and F1-score. The experimental outcomes showcased noteworthy levels of accuracy, affirming the model's adeptness in accurately categorizing retinal images into various stages of diabetic retinopathy. Moreover, the model's efficiency was assessed in terms of computational resource utilization and inference time, underscoring its potential for practical deployment in clinical settings.

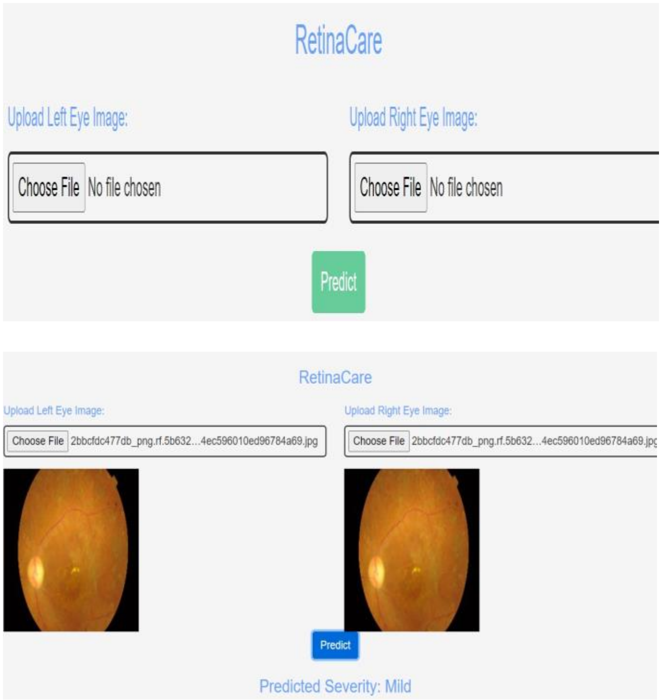

Fig.2: mild stage of the diabetic retinopathy

The above figure is classified as being in the mild stage of the diabetic retinopathy.

5. Conclusion

In conclusion, this study showcases the successful implementation of a Convolutional Neural Network (CNN) in categorizing severity levels of diabetic retinopathy. The model, trained on retinal images, accurately distinguishes between Mild to Severe cases. By leveraging advanced techniques like data augmentation and transfer learning, the model's robustness is strengthened. Integration into a user-friendly web application ensures convenient access to predictions. While the current model performs well, future enhancements can focus on dataset expansion and parameter fine-tuning to further enhance accuracy. These advancements suggest a bright future for improving early diagnosis and treatment of retinal disorders, highlighting the potential of AI in healthcare. The Future work involved in Collaborations with healthcare institutions aim to integrate the model into telemedicine platforms, while continuous updates ensure its relevance and effectiveness in diagnosing diabetic retinopathy, thereby enhancing patient outcomes and medical service provision.

References

[1] .Kocur, I., Resnikoff, S.. Visual impairment and blindness in Europe and their prevention. Brit J Ophthalmol (2002).
[2] Sculpher, M., Buxton, M., Ferguson, B., Spiegelhalter, D., Kirby, A.. Screening for diabetic retinopathy: A relative cost-effectiveness analysis of alternative modalities and strategies. Health Econ (1992).
[3] M. Alban and T. Gilligan, “Automated detection of diabetic retinopathy using fluorescein angiography photographs,” Stanford Technical Report, (2016).
[4] V. Gulshan, L. Peng, M. Coram, M. C. Stumpe, D. Wu, A. Narayanaswamy, S. Venugopalan, K. Widner, T. Madams, J. Cuadros, R. Kim, R. Raman, P. C. Nelson, J. L. Mega, and D. R. Webster, “Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs,” The Journal of the American Medical Association, vol. 316, issue (22, Dec. 2016).
[5] Mookiah, M.R.K., Acharya, U.R., Chua, C.K., Lim, C.M., Ng, E., Laude, A.. Computer-aided diagnosis of diabetic retinopathy: A review. Comput Biol Med (2013).
[6] Acharya, R., Chua, C.K., Ng, E., Yu, W., Chee, C.. Application of higher order spectra for the identification of diabetes retinopathy stages. J Med Syst (2008).
[7] Acharya, U., Lim, C., Ng, E., Chee, C., Tamura, T.. Computer-based detection of diabetes retinopathy stages using digital fundus images. P I Mech Eng H (2009).
[8] Fleming, A.D., Philip, S., Goatman, K.A., Prescott, G.J., Sharp, P.F., Olson, J.A.. The evidence for automated grading in diabetic retinopathy screening. Current Diabetes Reviews (2011).