A Deep Learning Based Approach for Classification of Diabetic Retinopathy

Astamai Murmu, Prayag Sing and Vineeth Piyush

October 29, 2023

A Deep Learning Based Approach for Classification of Diabetic Retinopathy

Astamai Murmu[1], Prayag Sing[2], Vineeth Piyush[3]
JLD College of Engineering and Management, Ramdhari, West Bengal[1,2]
College of Engineering, Keonjhar, Odisha[3]

Abstract - Diabetes Mellitus (DM) is a metabolic disorder happens because of high blood sugar level in the body. Over the time, diabetes creates eye deficiency also called as Diabetic Retinopathy (DR) causes major loss of vision. In recent times computer vision with Deep Neural Networks can train a model perfectly and level of accuracy also will be higher than other neural network models. In this study fundus images containing diabetic retinopathy has been taken into consideration. This paper proposes an automated knowledge model to identify the key antecedents of DR. We have tested our network on the largest publicly available Kaggle diabetic retinopathy dataset, and achieved 0.851 quadratic weighted kappa score and 0.844 AUC score, which achieves the state-of-the-art performance on severity grading. In the early-stage detection, we have achieved a sensitivity of 98% and specificity of above 94%, which demonstrates the effectiveness of our proposed method. Our proposed architecture is at the same time very simple and efficient with respect to computational time and space are concerned. The Deep Learning models are capable of quantifying the features as blood vessels, fluid drip, exudates, hemorrhages and micro aneurysms into different classes. The foremost challenge of this study is the accurate verdict of each feature class thresholds. The model will be helpful to identify the proper class of severity of diabetic retinopathy images.

Keywords - Computer-aided diagnosis, Diabetic retinopathy, Deep neural network, Convolutional neural network

1. Introduction

There has been a widespread observation of significant expectations for the development of advanced CAD systems. In order to address the healthcare needs on a global scale, computer-aided detection (CAD) systems have become indispensable technologies that aid in the timely identification and diagnosis of diseases. Diabetes has emerged as a prevalent and broad global health concern. It arises from the malfunctioning of the pancreas, a vital organ responsible for producing an inadequate amount of insulin. This deficiency in insulin gradually affects the human retina. In a recent publication, the World Health Organization (WHO) has presented a report that forecasts diabetes will ascend as the seventh leading cause of mortality by the year 2030. The abnormalities resulting from diabetes give rise to a medical condition known as diabetic retinopathy (DR). The prevalence of diabetic retinopathy has experienced significant growth on a global scale. This can be attributed to the ineffective metabolism of glucose, which greatly enhances the likelihood of chronic infection, particularly inside the human retina. Diabetic retinopathy (DR) is a prevalent and well observed ocular condition that arises as a consequence of retinal vascular injury. In significant instances, there is an occurrence of blood vessel dilation and subsequent fluid leakage, which can be observed as a manifestation of retinal pathological change.

The utilization of ocular fundus pictures. Exudates represent the prevailing and inclusive manifestations of diabetic retinopathy (DR). Microaneurysms and hemorrhages commonly occur within the human retina, accompanied by the secretion of exudates onto its surface. The morphology, dimensions, and overall visual characteristics of these features are indicative of the extent of the pathological condition. Proliferative diabetic retinopathy (PDR) is a stage of retinopathy characterized by the growth of blood vessels. On the contrary, non-proliferative diabetic retinopathies (NPDR) pertain to the early stage of diabetic retinopathy (DR) and can be classified into three main phases: mild, moderate, and severe NPDR. In general, mild non-proliferative diabetic retinopathy (NPDR) is characterized by the presence of a minimal number of micro-aneurysms. Moderate NPDR implies the presence or occurrence of hemorrhages, micro-aneurysms, and hard exudates. The severe phase of NPDR refers to the entire blockage of the retinal blood vessels. Diabetic retinopathy (DR) is characterized by the presence of certain visual markers, including exudates, hemorrhages, and microaneurysms, inside the retinal tissue of individuals affected by diabetes. The types of diabetic retinopathy compliant with its severity of DR are presented in Fig. 1.

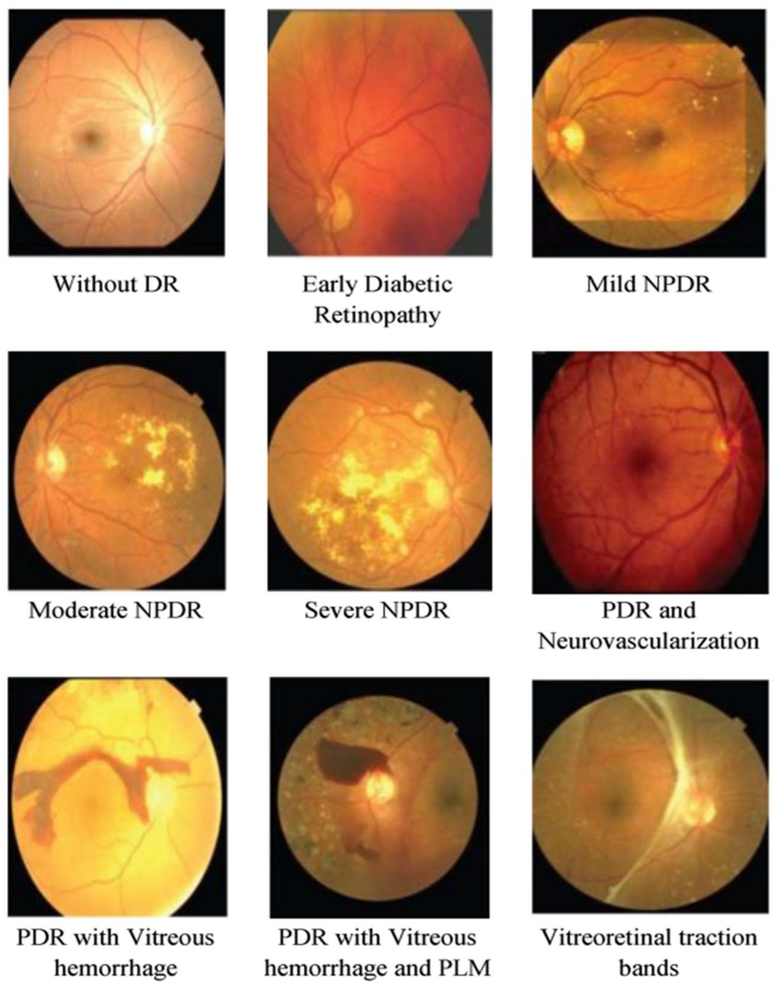

Figure 1. Different Stages of DR

2. Related Work

Diabetic and Malarial Retinopathy datasets are accessible. Many authors suggested using morphological operations and segmentation to discover blood vessels, micro aneurysms, etc.

Principal Component Analysis improves feature selection. For diabetes and non-diabetic picture classification, back-propagation NN and one-rule classifiers were used. M. Usman Akram et al. [3] use a hybrid classifier to detect retinal lesions by preprocessing, extracting lesions from candidates, formulating features, and classifying. The work extends m-Mediods-based modeling with Gaussian Mixture Model to create a hybrid classifier to improve classification accuracy. Winder et al. [5] study of digital color retinal pictures using algorithms for automated retinopathy identification. The algorithms studied were divided into five stages: preprocessing, optic disk localization and segmentation, retinal vasculature segmentation, macula and fovea localization, and retinopathy segmentation. Salman, et al. [6] review advanced methods for automatic anatomical feature extraction from retinal images to aid glaucoma diagnosis. They critically assessed automatic extraction methods using CDR, RNFL, and PPA characteristics. This improved Glaucoma diagnosis feature extraction approaches. Mookiah et al. [11] compared DR image detecting methods. The publication provides a comprehensive overview of DR image detecting methods. The paper precisely tallied possible techniques and accuracy results. Gardner et al. tested neural networks to see if they could detect diabetes characteristics in fundus images and compare them to ophthalmologist screening sets. The study found hemorrhages, exudates, and vessels. Compared to ophthalmologists, their network detected diabetic retinopathy more accurately. According to Roychowdhury et al., Adaboost feature ranking reduced the amount of features needed for lesion categorization [11]. They suggested a two-step hierarchical classification method that discards non-lesions or false positives first. Bright lesions and cotton wool patches are classed as hard exudates in the second step. Red lesions are still hemorrhages and micro-aneurysms. Rakshitha et al. discuss contourlet, curvelet, and wavelet imaging modification approaches for retinal picture improvement. Thus, Vo et al. compare these three image transformations. They study discriminant texture features derived by color multi-scale uniform LBPs, which are descriptors on the two proposed hybrid and five common color spaces. Then, enhanced EFM, a Fisher Linear Discriminant, can evaluate the retrieved features. Diabetic and Malarial Retinopathy datasets are accessible. Prasad et al. suggested using morphological operations and segmentation to discover blood vessels, micro aneurysms, etc. Principal Component Analysis [5] improves feature selection. For diabetes and non-diabetic picture classification, back-propagation NN and one-rule classifiers were used.M. Usman Akram et al. [6] use a hybrid classifier to detect retinal lesions by preprocessing, extracting lesions from candidates, formulating features, and classifying. The work extends m-Mediods-based modeling with Gaussian Mixture Model to create a hybrid classifier to improve classification accuracy. Winder, R. John, et al. [7] study of digital color retinal pictures using algorithms for automated retinopathy identification. The algorithms studied were divided into five stages: preprocessing, optic disk localization and segmentation, retinal vasculature segmentation, macula and fovea localization, and retinopathy segmentation. Haleem, Muhammad Salman, et al. [8] review advanced methods for automatic anatomical feature extraction from retinal images to aid glaucoma diagnosis. They critically assessed automatic extraction methods using CDR, RNFL, and PPA characteristics. This improved Glaucoma diagnosis feature extraction approaches. Mookiah et al. [11] compared DR image detecting methods. The publication provides a comprehensive overview of DR image detecting methods. The paper precisely tallied possible techniques and accuracy results.

3. Methodology

In order to achieve appropriate characterisation of DR/non-DR, it is crucial to perform image preprocessing on fundus images, since they contain sensitive data that is essential for effective processing. The pre-processing approach is an essential step in the completion of the arrangement for identifying micro-aneurysm regions in the images. The primary characteristics, such as micro-aneurysms, would appear small and circular in nature. The pre-processing stage should be conducted in a manner that accurately measures and identifies micro-aneurysms and other relevant features without compromising the quality of the images [10-12]. This study implemented the recommendation proposed in order to achieve optimal characterization of DR/non-DR types. In their study, Antal et al. utilized an ensemble-based model in order to improve the detection of microaneurysms (MAs) within the human eye. In order to conduct MA detection, a combination of pre-processing techniques and candidate region detection and extraction methods were employed. Given the interchangeable nature of pre-processing methods, it is recommended by the authors to carry out pre-processing prior to showcasing potential region detection and feature extraction. The avoidance of alterations in the properties of the original fundus image is seen.

In order to address the issue of noisy images, the authors propose a method that involves implementing histogram equalization. This technique is employed to enhance the quality of the data, making it more acceptable for subsequent processes such as feature extraction and classification. Further information regarding the pre-processing procedures can be found in the reference [40]. After conducting pre-processing, it becomes essential to recognize the blood vessels and identify the relevant critical features. In this study, prior to conducting feature extraction, the initial step was the extraction of blood vessels, which was subsequently followed by the localization of the related regions of interest (ROIs). In order to accomplish this objective, the process of blood vessel segmentation has been executed. A concise overview of the segmentation approach utilized is provided in the subsequent sub-section.

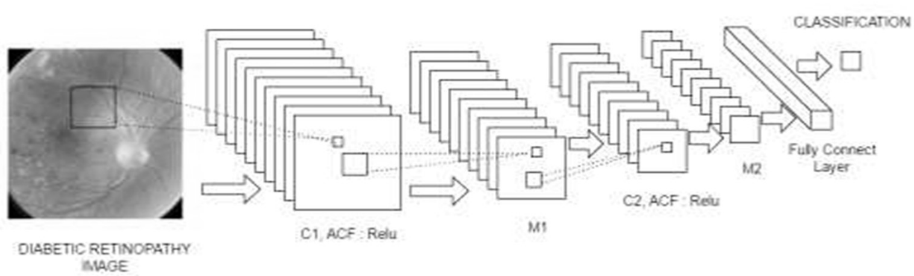

Figure 2. Proposed Framework

Table 1. Dataset description

Grade	Raw	Training	Validation
Normal	25810	25610	200
Mild NPDR	2443	2243	200
Moderate NPDR	5292	5092	200
Severe NPDR	873	673	200
Proliferative DR	708	508	200
Total	35, 126	34, 126	1, 000

Table 2. Model Architecture

Layer Type	Kernel Size & Number	Stride	Output Shape
input	..	..	$(512, 512, 3)$
convolution	4 x 4 x 32	2	$(256, 256, 32)$
convolution	4 x 4 x 32	1	$(255, 255, 32)$
max-pooling	3 x 3	2	$(127, 127, 32)$
convolution	4 x 4 x 64	2	$(62, 62, 64)$
convolution	4 x 4 x 64	1	$(63, 63, 64)$
max-pooling	3 x 3	2	$(31, 31, 64)$
convolution	4 x 4 x 128	1	$(32, 32, 128)$
convolution	4 x 4 x 128	1	$(33, 33, 128)$
max-pooling	3 x 3	2	$(16, 16, 128)$
convolution	4 x 4 x 256	1	$(17, 17, 256)$
max-pooling	3 x 3	2	$(8, 8, 256)$
convolution	4 x 4 x 384	1	$(9, 9, 384)$
max-pooling	3 x 3	2	$(4, 4, 384)$
convolution	4 x 4 x 512	1	$(5, 5, 512)$
max-pooling	3 x 3	2	$(2, 2, 512)$
fully connected	1024	..	(1024)
fully connected	1024	..	(1024)
fully connected	1	..	(1)

The Convolutional Neural Network (CNN) model is only trained using image data. The network was provided with input photos that have been processed to contain only a single band, and these images were assigned specific levels. The VGGnet model has been widely regarded as the CNN model. The VGGnet model, as described in [39], is composed of convolutional (CONV) layers that execute 3x3 convolutions with a stride of 1 and a padding of 1. Additionally, it includes pooling (POOL) layers that perform 2x2 maxpooling with a stride of 2. The network does not have any padding. The network was trained with the assistance of a central processing unit (CPU). The rectified linear unit (ReLU) activation function has been employed. Convolutional layers are typically accompanied with Maxpool layers at the pooling stage, which serve to extract the most salient features from the picture pixels. VGGnet demonstrates high performance when applied to photos with dense features. According to the model, normalization layers are not utilized as they do not contribute to the improvement of model correctness.

4. Result and Analysis

The application of an image preprocessing method or technique yields an improved image with enhanced features, as depicted in Figure 9. To obtain this enhanced image, a sequential procedure must be followed, wherein the output of each stage serves as the input for the subsequent phase, facilitating feature extraction. The removal of high intensity background noise in an image can result in a reduction of noise levels, while simultaneously emphasizing features that exhibit significant variations in pixel intensity values. The processed image undergoes a conversion to the RGB color space, resulting in an enhanced representation that provides improved visual information for a given image. The RGB image is subsequently partitioned into three distinct layers, namely the red, green, and blue layers. The GREEN layer is the outcome of the image preprocessing approach, which serves to emphasize the presence of exudates, white lesions, and veins within the image. The processes of morphological image processing conducted in the study are depicted in Figure 9. Both the statistics image data and processed images undergo training using BNN and DNN models. A total of 1000 retinopathy photos were included in both models. The reason for the negative impact of inadequate training on the performance of a binary neural network (BNN) model is attributed to the presence of a single layer hidden layer. The DNN model exhibits a shorter training time and higher accuracy in comparison to the BNN model. Deep neural networks (DNN) demonstrate high accuracy in hyperparameter adjustment for both statistical data and processed picture data. The Convolutional Neural Network (CNN) is widely regarded as a model of high quality for image recognition tasks. In this particular case, the CNN was trained using a dataset consisting of 1000 photos, achieving an accuracy rate of 72.5% when utilizing the VGGnet model. The utilization of CPU support in the training process has a significant effect on the duration of training. In order to evaluate the performance of the model, a dataset consisting of 300 photos was utilized. The results indicate that the model accurately predicted both normal retinopathy images and proliferative diabetic retinopathy images. The occurrence of misclassification was predominantly observed in photos categorized as level 1-2. Figure 10 displays the probabilistic outcome of picture categorization using a Convolutional Neural Network (CNN) model.

Table 3. Results Obtained

DR Grade	Grade Name	Total Images	Percentage
0	Normal	25810	73.84%
1	Mild NPDR	2443	6.96%
2	Moderate NPDR	5292	15.07%
3	Severe NPDR	873	2.43%
4	Proliferative DR	708	2.01%

5. Conclusions

This research introduces a unique deep neural network based on convolutional neural networks (CNN) for the detection of early-stage and severity grades of diabetic retinopathy in retinal images. In our study, it has been observed that in the absence of extensive data augmentation, a network with a high capacity is prone to error, even with the implementation of data augmentation techniques, it is possible for any neural network to exhibit overfitting when dealing with oversampled. Therefore, the incorporation of L2 regularization and dropout techniques holds considerable significance in the development of a small capacity network for retinopathy. In this study, we have presented a convolutional neural network (CNN) architecture with a 4x4 kernel size. Additionally, we have incorporated several preprocessing and augmentation. The network demonstrated a sensitivity of 98% and a specificity of over 94% in the early-stage detection task, as well as a kappa score over 0.The experimental findings have proved the effectiveness of our suggested algorithm to be sufficiently high for its utilization in clinical applications.

References

[1]. Mukherjee, N., Sengupta, S. Application of deep learning approaches for classification of diabetic retinopathy stages from fundus retinal images: a survey. *Multimed Tools Appl* (2023). https://doi.org/10.1007/s11042-023-17254-0

[2]. D. K. Prasad, L. Vibha and K. R. Venugopal, "Early detection of diabetic retinopathy from digital retinal fundus images", Intelligent Computational Systems (RAICS), 2015 IEEE Recent Advances in. IEEE, (2015).

[3]. M. U. Akram, "Detection and classification of retinal lesions for grading of diabetic retinopathy", Computers in biology and medicine, vol. 45, (2014), pp. 161-171.

[4]. Mukherjee, Nilarun, and Souvik Sengupta. "Comparing deep feature extraction strategies for diabetic retinopathy stage classification from fundus images." Arabian Journal for Science and Engineering (2023): 1-20.

[5]. R. J. Winder, "Algorithms for digital image processing in diabetic retinopathy", Computerized Medical Imaging and Graphics, vol. 33, no.8, (2009), pp. 608-622.

[6]. Mu. S. Haleem, "Automatic extraction of retinal features from colour retinal images for glaucoma diagnosis: A review", Computerized medical imaging and graphics, vol. 37, no. 7, (2013), pp. 581-596.

[7]. Mukherjee, N., and S. Sengupta. "A Hybrid CNN Model for Deep Feature Extraction for Diabetic Retinopathy Detection and Gradation." *International Journal on Artificial Intelligence Tools* (2023).

[8]. S. Roychowdhury, D. Koozekanani and K. Parhi, "Dream: Diabetic retinopathy analysis using machine learning", IEEE Journal of Biomedical and Health Informatics, vol. 18, no. 5, (2014), pp. 1717–1728.

[9]. M. R. K. Mookiah, "Computer-aided diagnosis of diabetic retinopathy: A review", Computers in biology and medicine, vol. 43, no. 12, (2013), pp. 2136-2155.

[10]. Mukherjee, N., Sengupta, S. (2022). Comparing Different Preprocessing Techniques for the Classification Tasks in Diabetic Retinopathy from Fundus Images. In: Mandal, J.K., Buyya, R., De, D. (eds) Proceedings of International Conference on Advanced Computing Applications. Advances in Intelligent Systems and Computing, vol 1406. Springer, Singapore. https://doi.org/10.1007/978-981-16-5207-3_51

[11]. NCD Risk Factor Collaboration, "Worldwide trends in diabetes since 1980: a pooled analysis of 751 population-based studies with 4· 4 million participants", The Lancet, vol. 387, no. 10027, (2016), pp. 1513-1530.

[12]. Mukherjee, Nilarun, and Souvik Sengupta. "In Search for the Optimal Preprocessing Technique for Deep Learning-Based Diabetic Retinopathy Stage Classification from Retinal Fundus Images." In *Artificial Intelligence Technologies for Computational Biology*, pp. 161-176. CRC Press, 2022.