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RESEARCH ARTICLE

DEEP LEARNING-BASED DIABETIC RETINOPATHY FOR CLASSIFYING RETINAL IMAGES

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Abstract – Diabetic retinopathy (DR) is a frequent eye disorder mostly affecting diabetics. It affects millions of individuals worldwide and is the leading cause of blindness and visual impairment in diabetics. DR occurs when excessive blood sugar levels damage the retina's small blood vessels. In this paper a novel deep learning-based approach for classifying retinal images into three categories: normal retina, good retina, and bad retina. The proposed system utilizes convolutional neural networks (CNNs) for automated feature extraction and classification. The pipeline begins with image preprocessing, including rescaling, train-test splitting, and data augmentation, to enhance model performance and generalization. The preprocessed images are then fed into a CNN model, which extracts features using several convolutional layers, ReLU activation, and pooling layers to minimize spatial dimensionality. The collected features are flattened and processed through fully linked layers, resulting in a SoftMax activation function that produces probabilistic classification results. The accuracy of the suggested method can reach 99.04%, compared to 83.1%, 83%, and 92.1% for conventional models like the Structured learning, High speed detection, and Fuzzy broad learning. In comparison to the existing approaches, the accuracy of the suggested methodology increased by 16.09%, 13.8%, and 3.75%, respectively.

***Keywords** – Diabetic Retinopathy, convolutional neural networks.*

1. INTRODUCTION

Medical imaging is the use of various imaging techniques to observe the inside structures and processes of the human body for diagnostic and therapeutic reasons. It is critical in modern healthcare because it gives detailed and non-invasive visual data that aids in illness detection, diagnosis, and treatment planning [1]. Human retina fundus pictures [2] are high-resolution photographs of the inside of the eye, especially the retina, taken with specialist imaging methods. Fundus pictures give important information on the health and condition of the retina, which aids in the diagnosis and treatment of a variety of eye illnesses. Retina fundus pictures show major anatomical components as the OD, macula, blood vessels, and different retinal layers. These images are acquired through a non-invasive procedure called fundus photography, where a specialized camera captures a wide-angle view of the retina after dilating the pupil and using a bright flash of light to illuminate the back of the eye.

The purpose of fundus photography is to provide a detailed visual record of the retina, which plays a crucial role in the diagnosis and management of various eye diseases. It helps ophthalmologists assess the health of the retina, identify abnormalities, and monitor changes over time. OD segmentation is essential for computer-aided diagnostic systems. The optic disc, sometimes referred to as the optic nerve head, is a circular area where blood vessels emerge and the optic nerve enters the eye. In recent years, convolutional neural networks (CNNs), fuzzy wide learning, and deep learning (DL) techniques have demonstrated encouraging outcomes in optic disc segmentation. These models are trained on annotated retinal images, where human experts manually outline the optic disc boundaries for supervision [3]. The major contribution of the work has been followed by

- The primary objective of a work is developing a DL-based model utilizing CNNto classify retinal images into normal, good, and bad retina categories, aiding in early diagnosis of retinal diseases.
- Implemented essential preprocessing techniques such as rescaling, train-test splitting, and data augmentation to enhance model accuracy and generalization.
- Utilized CNN layers with ReLU activation and pooling operations for efficient feature extraction, followed by full connected layers and a SoftMax activation function for classification.

The remaining portion of the work has been followed by section 1 represents the introduction section 2 illustrates the literature review, section 3 depicts the proposed methodology, section 4 illustrates the result and discussion and section 5 depicts the conclusion of this work.

2. LITERATURE REVIEW

Wang et al. [4] established a coarse-to-fine DL framework based on the U-net aproach of a traditional CNN to precisely identify the optic disc. The segmentation findings from the full image were divided into two different groups after this network was trained independently on the grayscale vessel density maps and color fundus images. DIARETDB0, DIARETDB1, DRISONS-DB, MESSIDOR, ORIGA, and DRIVE datasets are used in this method. The segmentation performance achieved by the given framework was largely trustworthy. The shortcoming of this method is the involvement of only low-resolution images for this analysis and the ground truth for the optic disc not identified precisely in color fundus images.

Ramani et al. [5] evaluated enhanced image processing method, automatic OD identification and segmentation is made possible. It divided into four stages, including Image pre-processing, optic disc localization, optic disc segmentation, and performance evaluation, each of which has a distinct set of operations that must be carried out. A variety of image processing method were used to enhance optic disc segmentation accuracy and optic disc localization performance. The quality of this method is its less computation time. The limitation of this method is the less disc localization performance in the messidor dataset.

Wang et al. [6] described a deep learning network that can recognize OD areas automatically. It defined a special sub-network and a decoding convolutional block based on the traditional U-Net framework. The uprightness of this methodology is to increase the OD regions accurate and reliable segmentation on color fundus images. The disfavor of this method is it segmented only the fundus OD regions.

Veena et al. [7] established the segmentation of OD and OC for the automated identification of glaucoma. The deep learning architecture method with an improved version of the two CNN models for OD and OC separately produces an accurate segmentation result. More image features can be recovered by multiplying the layers in both the CNN models. The DRISHTI-GS database is used to trained and tested this method. The positive side is multiple medical image segmentation applications can use this unique methodology. This negative side is quite time-consuming.

Ahmed et al. [8] expected to identify the midpoint of the optic disc by using the retinal image's mean intensity value. The method can be applied to improve the identification of retinal optic discs or to diagnose retinal disorders. An RGB fundus image's green channel is used to locate the optic disc center position using a candidate-based approach. Five publicly accessible databases have been used to examine the system. The merit of this approach is its reliability workflow and consumes less time. The demerit of this approach is its computational complexity.

Ali et al. [9] revealed a fuzzy wide learning system approach for glaucoma screening that uses OD and OC segmentation. The effective training process is a consequence of the technique. Another drawback is that, unlike some other approaches that operate directly on RGB fundus pictures, the segmentation of the red channel for OD and the green channel for OC requires the extraction of individual channels.

Fan et al. [10] illustrated a structured learning-based system for detecting OD. On the basis of structured learning, a classifier model is developed. The OD edge map is then obtained using the model. The edge map is threshold, and the result is a binary image of the OD. At last, the OD border is simulated by a circle using the circle Hough Transform (HT). This approach is evaluated three datasets Messidor, Drions, and ONHSD. The sufficient of this approach is performs effectively with cutting-edge techniques and serves as a reliable tool for OD segmentation. The negative side is it not combines the benefits of structured labelling with deep learning to train the edge detector.

Table 1. Merits And Demerits

Authors	Journal	Year	Merits	Demerits
Wang et al.	Elsevier	2019	The segmentation performance achieved by the given framework was largely trustworthy	The shortcoming of this method is the involvement of only low-resolution images for this analysis.
Ramani et al.	Elsevier	2020	The quality of this method is its less computation time.	The limitation of this method is the less disc localization performance in the messidor dataset.
Wang et al.	Elsevier	2021	The uprightness of this methodology is to increase the OD regions accurate and reliable segmentation on color fundus images.	The disfavor of this method is it segmented only the fundus OD regions
Veena et al.	Elsevier	2022	The positive side is multiple medical image segmentation applications can use this unique methodology.	This negative side is quite time-consuming.

Ahmed et al.	Springer	2015	The merit of this approach is its reliability workflow and consumes less time.	The demerit of this approach is its computational complexity.
Ali et al.	IEEE	2021	The effective training process is a consequence of the technique.	One of the technique's shortcomings is that it requires pre-processing and post-processing in order to get the desired result.
Fan et al	IEEE	2018	The sufficient of this approach is performs effectively with cutting-edge techniques and serves as a reliable tool for OD segmentation.	The negative side is it not combines the benefits of structured labelling with deep learning to train the edge detector.

3. PROPOSED METHODOLOGY

In this section a novel deep learning-based approach for classifying retinal images into three categories: normal retina, good retina, and bad retina has been proposed. Figure 1 illustrates the proposed methodology

3.1. Dataset Description

This work uses three datasets: the Ocular Disease Intelligent Recognition (ODIR) dataset, the EyePACS dataset, and the APTOS dataset from China, the United States, and India, respectively. This study solely uses the normal and PrDr retinal databases for the APTOS and EyePACS datasets. The normal retina is classified as class 0 and the PrDR as class 1. A valid and dependable method for determining the severity of DR is the APTOS DR severity scale. It has been widely used in clinical practice and research throughout Asia-Pacific. The 3662-training data are retrieved for this investigation because the test phase data lacks particular labels. It contains 295 class 1 photos and 1805 class 0 images. According to the statistics, class 0 has around six times as many photos as class 1. Shanggong Medical Technology Co., Ltd., Shanghai, China, gathered data on 5000 patients from several hospitals to create a Chinese dataset known as ODIR. This dataset contains 14,400 images. Only DR is taken into account in this study, which includes 1608 retinal images with DR and 2873 normal retinal images.

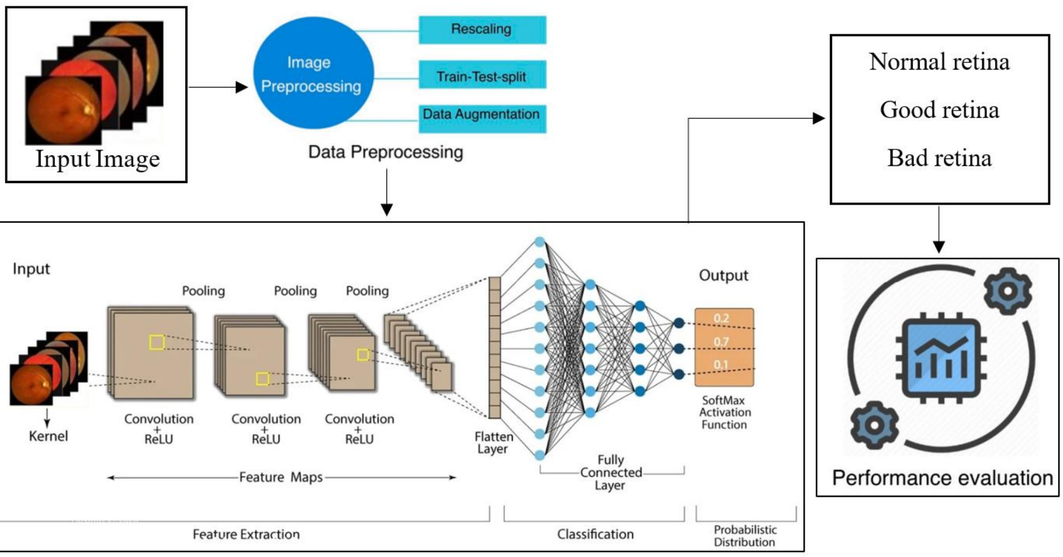

Figure 1. Proposed Methodology

3.2. Data Pre-Processing

The dataset is considered unbalanced if the data set for the first class is significantly smaller than the data set for the second class in a binary classification project [59,60]. The class with the least amount of information is the minority. On the other hand, the majority of the class is said to have a wealth of knowledge. This disproportion distribution significantly impairs the prediction process's performance, especially for the minority class, where it biases the approach and lowers its learning capacity. This situation may be acceptable in some applications, but it can compromise the validity of the model in real-world applications. There are different types of data augmentation techniques, but the most popular approach is geometric transformation, which has been used to address the class imbalance issue in the selected datasets in this study.

3.3. Classification via Hybrid DNN and one-dimensional DCNN

The DNN usually comprises of layered multilayer perceptrons (MLPs), with an enabled forward propagation procedure that exports inputs sequentially between the layers. By using gradient descent for automated (supervised) learning, DNNs may minimize the squared error in the anticipated outputs through weight backpropagation. One may argue that it is impossible to overstate the benefits of parallel hybrid networks in terms of efficiency and dependability, particularly when it comes to classification challenges. However, a number of factors come into play that might raise computing costs, decrease the model's potential for transferability, and enhance overfitting and model stochasticity.

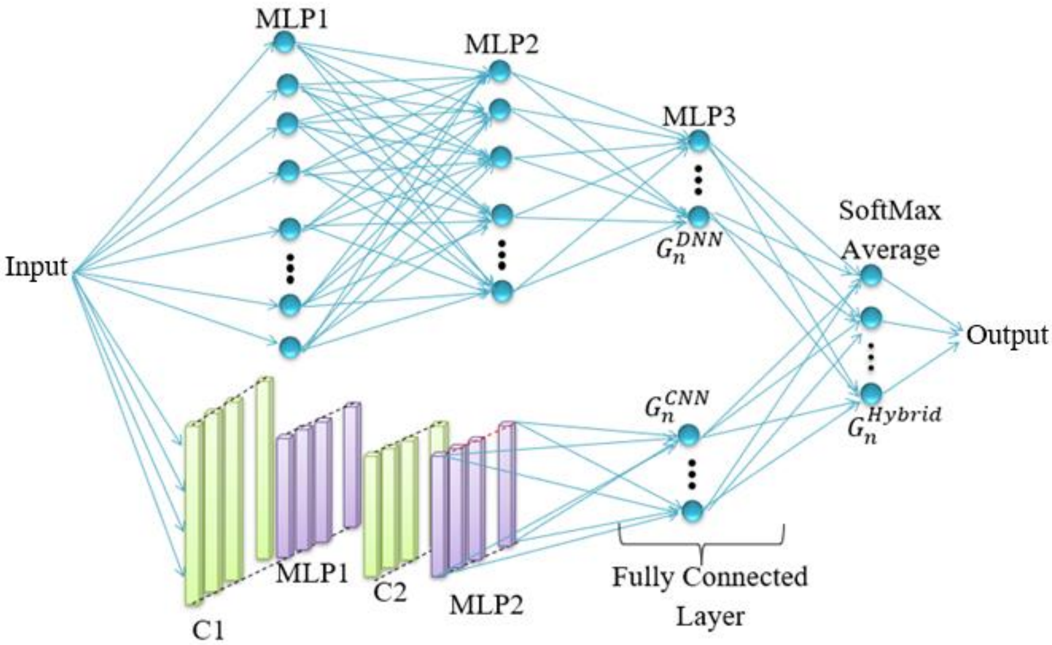

Figure 2. Hybrid DNN and one-dimensional DCNN

The entire one-dimensional CNN and hybrid DNN process is shown in Figure 2. Thus, a special DL-based FDI tool, the hybrid D-dCNN, has a two-branched tree structure. A more dependable paradigm for producing empirical judgments is offered by each branch, which separately extracts high-level discriminative characteristics from various data formats. Each model forecasts the likelihood of class labels using the SoftMax activation function, and the final prediction is generated by averaging the probabilities of the same class label. High-level properties are concurrently sent from the component models to the SoftMax-averaging layer.

Given a set of multi-class inputs $A_m^n = \{(A_1, B_1), (A_2, B_2), \ldots, (A_m, B_m)\}$, where $A_m \in G^n$ and $B_m \in \{1,2,\ldots,m\}$, as inputs, Equations (3) and (4) provide a summary of the CNN and DNN models' SoftMax-activated predictions, respectively.

$$G_m^{CNN} = CNN[SoftMax \otimes A_m^n] \quad (3)$$

$$G_m^{CNN} = DNN[SoftMax \otimes A_m^n] \quad (4)$$

Equation is used to average the outputs from both branches of the hybrid model

$$G_m^{Hybrid} = \sum_{i=1}^{2} \frac{G_m^{CNN} \oplus G_m^{DNN}}{2} \quad (5)$$

The suggested model's stochastic learning process necessitates a fair number of learning iterations to assure cost function reduction, as does that of existing ANNs. Equation (6) defines the categorical cross entropy, which is a fitting loss function for multi-class situations.

$$L_{CE} = -\sum_{i=1}^{M} T_i \log\left(R_m^{Hybrid}\right) \quad (6)$$

The objective is to continuously reduce LCE, which ensures accurate input-label modeling. By looking at the model's training convergence throughout the iteration phase, this may be visually verified. Additionally, cross validation evaluates the model's reliability across several trials while ensuring that a well-trained model is generated. This gives a model's accuracy range or horizon on the test data and removes the chance of accidental success and overfitting/underfitting issues.

4. RESULT AND DISCUSSION

This section discusses performance in terms of different assessment criteria and analyzes the experimental results of the proposed method. An i5 CPU and 4 GB of RAM were utilized to run the Python simulator to assess the effectiveness of the proposed model.

Table 2. Performance Evaluation

Method Name	Performance Evaluation
Deep learning framework based on U-Net [4]	Medium
Segmentation technique [5]	Good
Deep learning network [6]	Very high

Deep Learning convolutional neural network [7]	Excellent
Fuzzy broad learning [8]	Low
High speed detection technique [9]	Good
Structured learning based system [10]	Medium

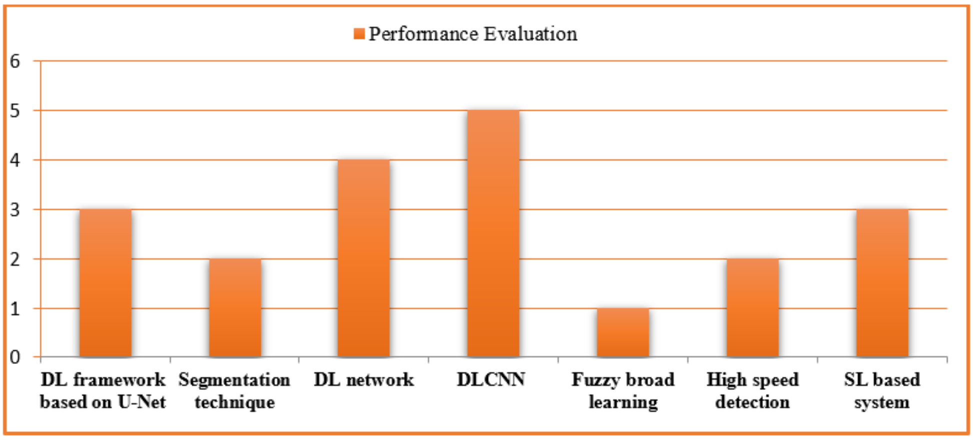

Figure 3. Chart for Performance Evaluation

Here, the above Table II and Figure 2 reveal the performance evaluation of OD segmentation techniques in retinal fundus images. Both, DL network [6] and DLCNN [7] methods explicit the 'Very high' and 'Excellent' result in the performance evaluation and noted the value '5' for Excellent and '4' for very high. Segmentation technique and High-speed detection framework have exposed the result as 'Good' is noted as 3. Deep learning framework based on U-Net approach and Structured learning-based system method are revealed the result as medium is noted as 3. The outcome of Fuzzy broad learning method shows the least performance in this performance evaluation.

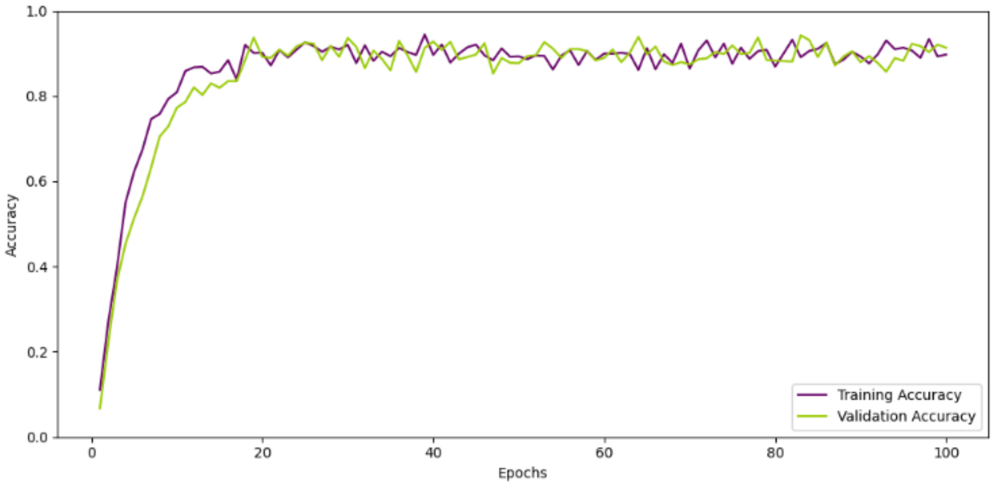

Figure 4. Accuracy Graph of the proposed methodology

The accuracy and repetition of the proposed model are depicted in Figure 6. Plotting the Y-axis against the X-axis depicts the overall quality of the epoch. The orange line here illustrates the testing period, and the violet line shows the training value of the proposal model.

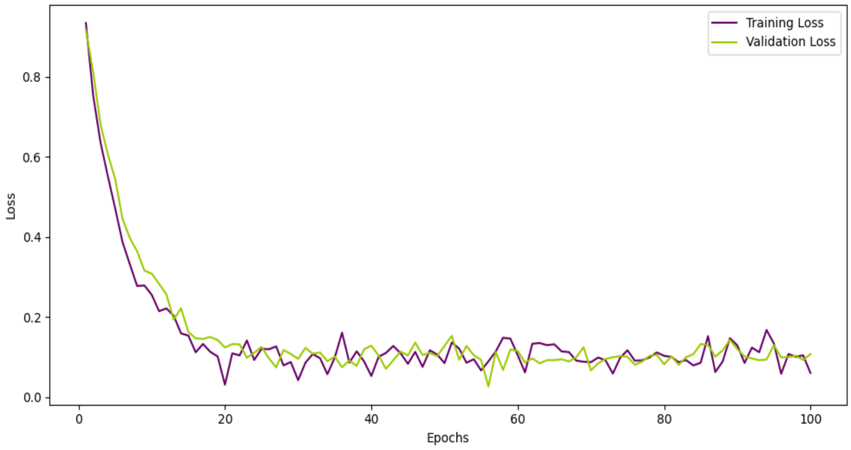

Figure 5. Loss Graph of the proposed methodology

Figure 7 describes the loss and iteration graph of the proposed method. Plotting the Y-axis against the X-axis illustrates the overall quality of the epoch.

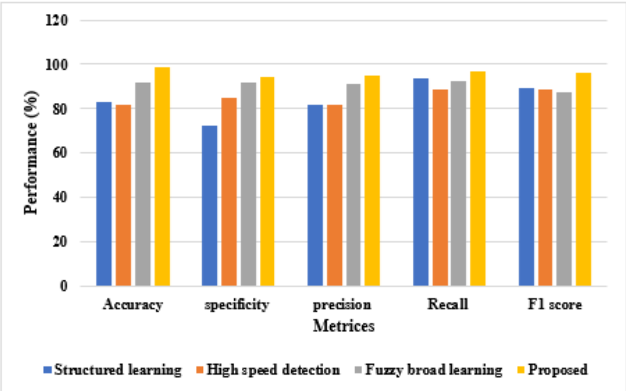

Figure 6. Performance Analysis

Figure 11 shows that the suggested strategy outperforms the alternative techniques in terms of performance. The accuracy of the suggested model can reach 99.04%, compared to 83.1%, 83%, and 92.1% for conventional models like the Structured learning [10], High speed detection [9], and Fuzzy broad learning [8]. In comparison to the current approaches, the accuracy of the suggested methodology increased by 16.09%, 13.8%, and 3.75%, respectively.

5. CONCLUSION

In this section a novel deep learning-based approach for classifying retinal images into three categories: normal retina, good retina, and bad retina. The proposed system utilizes CNN for automated feature extraction and classification. To improve model performance and generalization, the pipeline starts with picture preprocessing, which includes rescaling, train-test separation, and data augmentation. After that, the preprocessed photos are input into a CNN model, which uses pooling layers to minimize spatial dimensions and numerous convolutional layers with ReLU activation to extract features. After being flattened and run through fully connected layers, the retrieved features are sent into a SoftMax activation function, which produces probabilistic classification outputs. The accuracy of the suggested method can reach 99.04%, compared to 83.1%, 83%, and 92.1% for conventional models like the Structured learning [10], High speed detection [9], and Fuzzy broad learning [8]. In comparison to the existing approaches, the accuracy of the suggested methodology increased by 16.09%, 13.8%, and 3.75%, respectively. More research will be conducted in these areas in the future to improve the model's clinical usefulness and enable improved medical diagnostic decision-making because of accurate uncertainty estimations and effective calibration.

CONFLICTS OF INTEREST

This paper has no conflict of interest for publishing.

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