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A review: A Unified Deep Learning and Image Processing Approach for Diabetic Retinopathy Detection.

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ABSTRACT

Diabetic Retinopathy (DR) is an eye disease that damages the blood vessels in the retina, leading to vision impairment and potentially blindness if not detected in its early stages. DR is classified into five stages: normal, mild, moderate, severe, and Proliferative Diabetic Retinopathy (PDR). Traditionally, skilled ophthalmologists manually examine colored fundus images to diagnose DR, but this process is time-consuming and prone to human error. To address these limitations, various image processing techniques have been introduced to automatically detect DR and its progression from retinal images. However, many existing methods struggle to capture the complex features required for accurate classification, particularly in the early stages of DR, leading to low detection accuracy. we utilized advanced image processing techniques combined with deep learning to improve the detection of DR stages. Using the publicly available Kaggle dataset of retina images, we applied an ensemble of five deep Convolutional Neural Network (CNN) models (Resnet50, Inceptionv3, Xception, Dense121, Dense169) to extract rich features from the images. These features were processed using image enhancement, filtering, and segmentation techniques to improve the model's ability to detect all stages of DR. This paper reviews and analyzes state-of-the-art deep learning methods and image processing approach. Utilization of Deep learning algorithms has aided the early diagnosis of Diabetic Retinopathy(DR).

INDEX TERMS

Diabetic Retinopathy, Image Processing, Deep Learning, Convolutional Neural Networks, Classification.

1. INTRODUCTION

Diabetic Retinopathy (DR) is a severe complication of diabetes that damages the blood vessels in the retina, leading to vision impairment and even blindness if left untreated. As diabetes becomes more prevalent worldwide, the number of patients affected by DR is expected to rise dramatically. Early detection is critical in preventing the progression of the disease, but diagnosing DR, especially in its early stages, is challenging due to subtle visual differences in retinal images.

Diabetic Retinopathy (DR) is one of the major causes of blindness. DR mutilate the retinal blood vessels of a patient having diabetes. The DR has two major types: the Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR) [5]. The DR in the early stages is called NPDR which is further divided into Mild, Moderate, and Severe stages. Where the mild stage has one micro- aneurysm (MA), a small circular red dot at the end of blood vessels. In the Moderate stage the MAs rapture into deeper layers and form a flame-shaped hemorrhage in the retina. The severe stage contains more than 20

intraretinal hemorrhages in each of the four quadrants, having definite venous bleeding with prominent intraretinal microvascular abnormalities. PDR is the advanced stage of DR which leads to neovascularization, a natural formation of new blood vessels in the form of functional microvascular networks that grow on the inside surface of the retina. The figure, 1 visually presents the different stages of DR. It is clear from the given figure the Normal and Mild stage looks visually similar. Hence, it is difficult to detect the Mild stage.

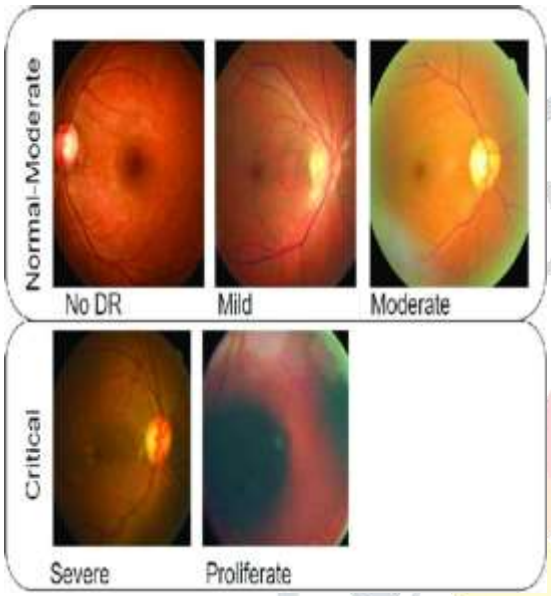

Figure 1: Different stages of DR

With the increasing number of diabetes cases globally, the prevalence of DR is expected to rise significantly in the coming years. Early detection and treatment are crucial to prevent the progression of DR to more severe stages, which can result in irreversible blindness. However, manual diagnosis through fundus images by trained ophthalmologists is both time-consuming and prone to error, especially in the early stages where symptoms are subtle.

Traditionally, the detection of DR relies on manual examination of retinal fundus images by trained ophthalmologists. However, this method is labor-intensive, time-consuming, and prone to human error. In particular, distinguishing between the early stages of DR, such as the Mild and Moderate forms, can be difficult, resulting in delayed treatment for patients.

Globally, the number of DR patients is expected to increase from 382 million to 592 million by 2025 [11]. A survey [11] conducted in the province of Khyber Pakhtunkhwa (KPK), Pakistan, report 30% of diabetes patients are affected by DR in which 5.6% succumbs to blindness. Over time, the mild NPDR develops into PDR if not controlled in the early stages.

In the early stages, DR usually has no symptoms, but as it progresses, patients may experience floaters, blurred vision, distortions, and loss of sight. This makes early detection crucial to prevent the severe stages. Fundus images (pictures of the inside of the eye) are commonly used to diagnose DR, but manual analysis by doctors is time- consuming and costly. Therefore, computer vision techniques have been developed to automatically analyze these images and help doctors. These techniques can be divided into

traditional feature extraction methods, like HoG, SIFT, and Gabor filters, and end-to-end learning methods. Traditional methods often struggle with changes in image scale, rotation, and lighting, while end-to-end learning models can automatically learn hidden features and perform better in classifying DR stages.

Although many methods have been used to detect DR in the Kaggle dataset, no method has been successful in detecting the Mild stage, which is critical for early treatment. This study aims to detect all stages of DR, including the Mild stage, using deep learning ensemble models. The results show that the proposed approach performs better than previous methods.

To overcome these limitations, a unified approach that combines the strengths of both deep learning and image processing techniques is proposed. Image processing techniques can enhance and segment retinal images to highlight key features such as microaneurysms and hemorrhages, while deep learning models can learn complex patterns and provide automated classification of DR stages.

In this study, we utilize a unified framework that integrates image processing for preprocessing and enhancement with an ensemble of deep learning models to detect and classify DR across all stages, including the Mild stage. By using the publicly available Kaggle dataset, we show that this hybrid approach improves detection accuracy and addresses key challenges faced by traditional methods, particularly in early- stage detection, offering a robust solution for automated DR screening.

2. RELATED WORK

As deep learning gained traction, convolutional neural

networks (CNNs) became popular for their ability to extract complex features automatically. Notable CNNs like AlexNet, Google Net, ResNet18, and ResNet50 were employed in various studies, offering improvements in detecting features like vessel irregularities.

The classification of DR has been extensively studied in the literature. Gondal *et al.* [5] proposed a CNN model for the referable Diabetic Retinopathy (RDR). They used two publicly available datasets Kaggle and DiaretDB1, where the Kaggle dataset is used for training and DiaretDB1 is used for testing. They are doing binary classification as normal and mild stages are considered as non-referable DR where the rest of the three stages are used as referable DR. The performance of the CNN model is evaluated based on binary classification resulting in sensitivity 93.6% and specificity 97.6%. Quelle et al. [19] proposed three CNN models for binary classification and detected DR lesions. They also used the Kaggle and DiaretDb1 dataset for training and testing respectively. Diabetic retinopathy has five (5) stages to classify the occurrence of diseases. The stage-wise classification is discussed by Chanrakumar and Kathirvel [2] introduced the CNN model with a dropout regularization technique trained on the Kaggle dataset and tested on DRIVE and STARE dataset. The accuracy achieved by their model is 94%. They manually performed an augmentation and preprocessing steps by using an image editing tool. Wang et al. [17] proposed a novel architecture that classifies the images as normal/abnormal, referable/ non-referable DR and gets the high AUC on a normal and referable DR task 0.978 and 0.960 respectively and specificity is 0.5. Their

proposed method uses three networks: main, attention and crop. The main network uses the Inception model that is trained on ImageNet where the attention network highlights different types of lesions in the images and crop network's crop the high attention image. Pratt *et* al. [11] proposed a CNN architecture used for classifying five stages but could not classify the mild stage accurately, due to the nature of architecture. Another limitation is that they used the skewed dataset of Kaggle that led to the high specificity with the tradeoff in low sensitivity. Yang et al. [14] proposed DCNN 83.68% accuracy. However, DR stages were not explicitly classified in their work. Saleh *et* al.

[6] presented an ensemble technique for DR risk assessment, which justifies the presence or absence of the disease. They prepared a dominance-based rough set balanced rule ensemble (DRSA-BRE) and compared their works with the random forest classifier. The best sensitivity score achieved was near 80%. Similarly, various DR detection methods have been presented in this field. However, none of these solve the problem of non- uniform illuminations, which can play a major role in detection of proliferative and Non-proliferative DR. Zhou et al. [2] presented a luminosity adjustment technique in which a luminance matrix is obtained by the gamma correction of value channel in HSV color space to improve the quality of individual RGB channels. For improving the contrast of images, contrast limited adaptive histogram equalization (CLAHE) technique was used that involves a kernel based iterative process to normalize the histogram of image pixels to avoid congestion of the pixels in a particular range, thus improving the image quality. Singh et al. [18] used the usual histogram equalization technique for low-radiance images to clip away the pixel-values based on the threshold, which was calculated by taking the average median value of the image to enhance the normalization results. They used structural similarity index measure and the Euclidean distance to validate their prediction results. Although numerous techniques proposed methodologies for image contrast enhancement, but none of them focused on image desaturation for developing a DR system.

3. TECHNIQUES

3.1 Image Processing Techniques

3.1.1 Segment Based Techniques

Thresholding: Used to segment foreground objects (e.g., blood vessels, microaneurysms) from the background by converting the image into binary form based on pixel intensity.

Edge Detection: Detects boundaries of important structures like retinal vessels. Techniques: Canny, Sobel, and Prewitt edge detectors.

Region-Based Segmentation: Segments the regions of interest such as exudates, hemorrhages, and microaneurysms.

3.1.2 Morphological Operations

Dilation and Erosion: Applied to enhance or remove certain structures like blood vessels or exudates.

Opening and Closing: Used to smooth the contours and fill small gaps in the vessel structure.

3.1.3 Feature Based Techniques

Local Binary Patterns (LBP): Captures texture information in retinal images, which can help in identifying different DR stages.

Histogram of Oriented Gradients (HoG): Extracts features related to the orientation and intensity of edges in the image.

Gabor Filters: Extracts texture features, which help in detecting lesions and abnormalities.

Wavelet Transform: Provides multi- resolution analysis to capture both spatial and frequency details of retinal images

3.1.4 Color Based Techniques

Color Space Transformation: Converts an image from one color model (RGB) to another (e.g., HSV or YCbCr).

Color Enhancement: Adjusts the hue, saturation, or brightness of color images.

Color Segmentation: Segments objects based on their color characteristics.

3.2 Deep Learning Techniques

3.2.1 Convolutional Neural Networks (CNNs)

A **CNN** is a type of deep learning model that is widely used for analyzing visual data. CNN is the most popular algorithm for DR classification. A commonly used type of CNN includes convolutional, pooling, and fully connected (FC) layers. Several kernels in each convolutional layer are used to generate feature maps; each feature map is down-sampled in the pooling layers to reduce the network parameters to accelerate the training process and avoid overfitting. Feature maps after flattening are used as input of FC layers, and the final CNN output result is obtained by passing the outputs of the last FC layer through the activation function. CNNs are extensively used for automatic feature extraction in retinal images, including models like AlexNet,

GoogLeNet, ResNet18, and ResNet50. These networks have been applied to detect neovascularization and other retinal abnormalities. [3]

Class Labels	Number of Images
No DR	1805
Mild	370
Moderate	999
Proliferate DR	295
Severe	193

3.2.2 Hybrid Models (ResNet18 + GoogLeNet)

A combination of ResNet18 and GoogLeNet is proposed for enhanced neovascularization detection, using a depth concatenation layer for improved feature extraction and classification accuracy.

3.2.3 Transfer Learning

Transfer learning is employed to adapt pre-trained networks (like AlexNet, GoogLeNet, and ResNet) for neovascularization detection in retinal images, minimizing the need for large training datasets.

4. DATASET DETAILS

Datasets are collections of data that can be used to train and test DL models, which is one of the key reasons for the success of DL research. However, in the field of fundus images, high-quality, accurate labeling, and sufficient dataset collection are challenging. One reason is that privacy protection of personal data makes it difficult to acquire and share medical. data. In addition, different fundus imaging equipment and settings, imaging characteristics, and operators lead to poor consistency in the image quality and standards. In addition, image labeling is commonly performed by professional ophthalmologists, but labeling standards are significantly inconsistent among different labelers.

Among the public datasets, MESSIDOR [8], Kaggle EyePACS [9], Kaggle APTOS
[10] and MESSIDOR-2 [13] are the most popular for DR classification.

Table1: Data Distribution.

The DDR dataset consists of 12522 images annotated by multiple experts according to ICDRSS. Although it is the second largest dataset for DR classification,

there is a significant imbalance in different DR severities; thus, it has not yet been widely used. Because most of these datasets are small, many studies have used different or combinations of them to train and validate DL algorithms [4], [15], [16].

Table2: Public datasets for DR.

Year	Dataset (Available link)	Country	Size	Resolution	Annotations	Device used	Tasks
2004	MESSIDOR[14]	France	1200	1440×960 2240×1488 2304×1536	Image level	Topcon TRC NW6	DR grading
2007	DIARETDB1[40]	Finland	89	1500×1152	Pixel level	Zeiss FF450+	DR grading Lesion detection
2009	Kaggle EyePACS[42]	United States	88702	Varying	Image level	Centervue DRS, Optovue iCam, CanonCR1 DG-CR2, Topcon NW	DR grading
2010	MESSIDOR-2[44]	France	1748	1440×960, 2240×1488, 2304×1536	Image level	Topcon TRC NW6	DR grading
2012	IRIS-MED[46]	United States	169	Varying	Pixel level	Zeiss Visucam PRO fundus camera	DR grading Lesion detection
2013	E-Ophtha[47]	France	463	2544×1696 1440×960	Pixel level	Canon CR DGi, Topcon TRC NW6	DR diagnosis Lesion detection

5. RESULTS AND DISCUSSIONS

5.1 PERFORMANCE METRICS

To quantitatively evaluate the proposed model we use accuracy, sensitivity, specificity, precision, F1 measures, AUC [1] and ROC [7] as performance metrics.

Accuracy: The accuracy can be calculated in terms of positive and negative classes:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \ldots.(1)$$

where TP (True Positives) is the number of correctly classified instances of the class under observation, TN (True Negatives) is the number of correctly classified instances of rest of the classes, FP (False Positives) is the number of miss-classified instances of rest of the classes and FN (False Negatives) is the number of miss-classified instances of the class under observation.

Recall/Sensitivity: It is the ratio of *TP* and *TP + FN*

$$Sensitivity = \frac{TP}{TP + FN}. \quad \ldots.(2)$$

Specificity: It is the ratio of *TN* and *TN + FP* Highlight

$$Specificity = \frac{TN}{TN + FP}. \quad \ldots.(3)$$

Precision: It is the ratio of *TP* and *TP + FP* Highlight.

$$Precision = \frac{TP}{TP + FP}. \quad \ldots.(4)$$

F1-Score: It is the weighted harmonic mean of precision and recall:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}. \quad \ldots.(5)$$

It returns the score between 0 and 1, where 1 means best score and 0 is the worst score.

Receiver Operating Curve (ROC)

[33]: Plots the true positive rate (TPR) against the false positive rate (FPR).

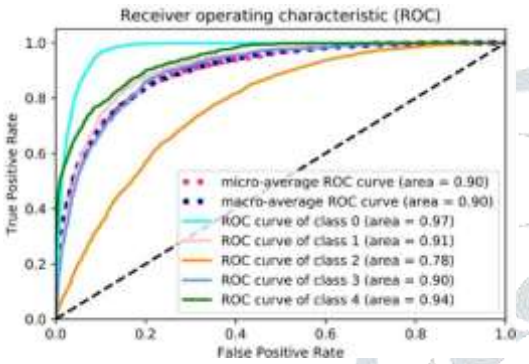

Figure2: ROC Curve.

Area Under the Curve (AUC)

[32]: It represents the degree or measure of separability of different classes. The higher the AUC score means the better the model and vice versa.

Imbalanced Dataset: Accuracy is a misleading metric when the dataset is highly imbalanced [20], it gives bias results. In our case, the accuracy achieved is biased towards the negative class which is class-0 (normal). So along with accuracy, we have also used other parameters such as Recall, Precision, Specificity, F1-score, and ROC-curve to provide unbiased results. The achieved accuracy, recall, specificity, precision, and F1-score are 80.8%, 51.5%, 86.72%,
63.85%
and 53.74% respectively.

	Recall	Precision	Specificity	F1-Score
Class-0	0.97	0.68	0.68	0.80
Class-1	0.54	0.73	0.73	0.62
Class-2	0.50	0.42	0.42	0.46
Class-3	0.61	0.64	0.64	0.63
Class-4	0.59	0.84	0.84	0.69

Table3: Performance measure of each class

6. CONCLUSION

Diabetes is a chronic medical condition that occurs when the body either doesn't produce enough insulin or cannot effectively use the insulin it produces. According to various studies, patients with diabetes have approximately a 30% likelihood of developing Diabetic Retinopathy (DR). DR progresses through multiple stages, ranging from mild to severe, eventually leading to Proliferative Diabetic Retinopathy (PDR). In the advanced stages, patients may experience symptoms such as floaters, blurred vision, and, if left undetected or untreated, complete blindness. Early detection is crucial to prevent vision loss. However, manual diagnosis of retinal images is time-consuming, requires specialized expertise, and can be challenging. To address this, computer vision-based techniques for the automatic detection of DR and its various stages have been developed, offering a faster and more efficient approach to diagnosis. These automated systems have shown potential in reducing the burden on healthcare professionals and ensuring timely treatment.

Author	Year	Title	Key Contributions
S. Qummar et al. [21]	2019	Deep Learning Ensemble Approach for Diabetic Retinopathy Detection.	It outperforms existing methods and accurately classifies all five stages of DR, including early stages.
Yi Chen, Rupeng Zhou, Meng Zhang. [25]	2021	A Novel Diabetic Retinopathy Detection Approach based on Deep Symmetric Convolutional Neural Network.	It improves the detection performance of microaneurysms using different filtering structures.
Michael Chi Seng, Ibrahim. [22]	2022	A Deep Learning Approach for the Detection of Neovascularization in Fundus Images Using Transfer Learning.	It outperforms individual CNN models and other deep learning methods using SVM for classification.
Jingbo Hu, Huan Wang. [30]	2022	Graph Adversarial transfer Learning for Diabetic Retinopathy Classification.	Model achieves high accuracy, specificity and sensitivity for DR.
Mohamed M. Farag, Mariam Fouad. [27]	2022	Automatic Severity Classification of Diabetic Retinopathy based on DenseNet and Convolutional Block Attention Module.	Proposed model achieved 97% accuracy, 97% sensitivity, 98.3% specificity.
Jabbar et al. [24]	2024	Lesion-based DR Detection through Hybrid Deep Learning Model.	Achieved high accuracy and effectiveness in detecting various types of lesions related to DR.
Harshit Kaushik, Manjit Kaur. [28]	2021	Diabetic Retinopathy Diagnosis from Fundus Image using Stacked Generalization of Deep Models.	This model achieved 97% accuracy for binary classification.
Rubina Rashid, Waqar Aslam, Imran Ashraf.[23]	2024	A Detectability Analysis of Retinitis Pigmentosa using Novel SE-ResNet based Deep Learning Model and Color Fundus Images.	This model achieved high performance metrics, including accuracies of 100%, 99.89%, on different datasets.
Saif Hammed Abbood, Amjad Rehman. [31]	2022	Hybrid Retinal Image Enhancement Algorithm for Diabetic Retinopathy Diagnostic Using Deep Learning Model.	The proposed algorithm enhances image quality, which improves feature extraction and classification accuracy for diabetic retinopathy diagnosis.
F. Saeed, et al. [26]	2021	Automatic Diabetic Retinopathy Diagnosis using Adaptive fine-tuned Convolutional Neural Network.	This model was re-initialized Gradient boosting classification.
Ester Parra-Mora, Alex Gordon. [29]	2021	Epiretinal Membrane Detection in Optical Coherence Tomography Retinal Images using Deep Learning.	Study achieved an accuracy of 99.7% with sensitivity and 99.4% specificity.

Table4: Literature Survey about Diabetic Retinopathy

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