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A HYBRID DEEP LEARNING MODEL FOR AUTOMATED DETECTION AND CLASSIFICATION OF DIABETIC RETINOPATHY FROM RETINAL FUNDUS IMAGES

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Abstract
Diabetic retinopathy is one of the most common microvascular complications of diabetes mellitus and remains a leading cause of preventable vision impairment worldwide. Early detection and timely intervention are important for reducing disease progression and preserving visual function. Retinal fundus imaging is widely used for screening diabetic retinopathy; however, manual assessment requires specialized expertise and may be challenging in large-scale screening programs. Recent advances in deep learning have demonstrated promising results in medical image analysis and automated disease detection. This study proposes a hybrid deep learning model for automated detection and classification of diabetic retinopathy using retinal fundus images. The framework combines convolutional neural network-based feature extraction with a feature fusion and classification module to improve discrimination across different disease stages. Image preprocessing techniques were applied to enhance retinal structures and reduce image variability before model training. The developed model was evaluated using publicly available retinal imaging datasets containing normal and diabetic retinopathy cases with multiple severity levels. Performance was assessed using accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve. Experimental results indicate that the proposed hybrid model effectively identifies retinal abnormalities associated with diabetic retinopathy and provides reliable classification across disease categories. The findings suggest that deep learning-based screening systems may support ophthalmologists in large-scale retinal assessment and facilitate earlier diagnosis. The proposed framework contributes to automated diabetic retinopathy screening by combining image-based learning with clinically relevant disease classification.

Keywords— Diabetic Retinopathy, Retinal Fundus Images, Deep Learning, Medical Image Analysis, Computer-Aided Diagnosis, Convolutional Neural Network, Ophthalmic Screening

I. INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder affecting millions of individuals worldwide and is associated with numerous long-term complications involving the cardiovascular, renal, nervous, and visual systems. Among these complications, diabetic retinopathy (DR) represents one of the most significant causes of vision impairment and blindness among working-age adults [1]. The condition develops as a consequence of prolonged hyperglycemia, which damages retinal blood vessels and leads to structural changes within retinal tissues. Early diagnosis and treatment are important because disease progression may occur before noticeable visual symptoms appear. Diabetic retinopathy is characterized by a range of retinal abnormalities, including microaneurysms, hemorrhages, hard exudates, cotton wool spots, venous abnormalities, and neovascularization [2]. These pathological changes progress through different stages, typically classified as mild, moderate, severe, and proliferative diabetic retinopathy. Accurate identification of disease severity is important for determining appropriate clinical management and follow-up strategies. Retinal fundus photography has become one of the most widely used imaging modalities for diabetic retinopathy screening. Fundus images provide visual information regarding retinal blood vessels, optic disc structures, macula regions, and pathological lesions associated with disease progression. Large-scale screening programs frequently rely on retinal imaging to identify individuals requiring specialist ophthalmological evaluation [3]. Despite its clinical utility, manual interpretation of retinal images presents several challenges. The increasing prevalence of diabetes has substantially increased the demand for retinal screening services. Manual examination requires trained ophthalmologists or retinal specialists and may be time-consuming when large numbers of images must be reviewed. Furthermore, interpretation may be influenced by image quality, observer variability, and workload constraints [4].

Computer-aided diagnosis systems have therefore attracted considerable attention as tools for supporting retinal image analysis. Early automated approaches relied on handcrafted image features describing vessel morphology, lesion characteristics, texture information, and color distributions. These methods demonstrated potential for diabetic retinopathy detection but often required extensive feature engineering and were sensitive to image acquisition conditions [5]. Recent developments in deep learning have transformed medical image analysis by enabling automatic feature learning directly from image data. Convolutional neural networks (CNNs) have achieved encouraging results in image classification, object detection, and segmentation tasks across a wide range of healthcare applications [6]. In ophthalmology, deep learning models have been applied to diabetic retinopathy detection, glaucoma screening, age-related macular degeneration assessment, and retinal vessel analysis [7]. Several studies have reported high classification performance for diabetic retinopathy detection using deep neural networks. However, challenges remain regarding generalization across datasets, class imbalance, image variability, and accurate discrimination among disease severity levels. In many clinical settings, distinguishing between different stages of diabetic retinopathy is as important as identifying the presence of disease itself. Models designed solely for binary classification may therefore provide limited clinical utility. Hybrid deep learning approaches have been proposed to address some of these limitations. By combining complementary feature extraction and classification strategies, hybrid models may improve representation learning and classification performance. Such approaches can capture both global retinal characteristics and localized pathological patterns associated with diabetic retinopathy progression [8]. Although previous studies have demonstrated the feasibility of automated diabetic retinopathy screening, there remains a need for models capable of reliable multiclass classification while maintaining consistent performance across heterogeneous retinal images. Additional evaluation of hybrid deep learning architectures may contribute to improved screening systems suitable for clinical deployment. This study proposes a hybrid deep learning model for automated detection and classification of diabetic retinopathy using retinal fundus images. The framework integrates image preprocessing, deep feature extraction, feature fusion, and multiclass classification within a unified architecture. The objective is to improve disease stage discrimination and support automated retinal screening.

II. RELATED WORK

Automated diabetic retinopathy detection has been an active area of research for more than two decades. Early studies focused on image processing techniques designed to identify retinal lesions such as microaneurysms, hemorrhages, and exudates from fundus photographs. These methods generally relied on handcrafted features extracted from retinal structures and lesion regions [5]. Niemeijer et al. [9] investigated automated detection of diabetic retinopathy lesions using machine learning classifiers and demonstrated that lesion-based analysis could

support screening applications. Similar studies explored vessel segmentation, optic disc localization, and texture-based representations to improve disease detection accuracy. The emergence of deep learning significantly advanced retinal image analysis. Gulshan et al. [7] demonstrated that deep convolutional neural networks could achieve high sensitivity and specificity in diabetic retinopathy screening tasks using large-scale retinal image datasets. Their work highlighted the potential of deep learning as a screening support tool in ophthalmology. Subsequent studies expanded the use of convolutional neural networks for diabetic retinopathy classification. Pratt et al. [10] developed a CNN-based framework capable of identifying multiple stages of diabetic retinopathy and reported encouraging classification performance. Similar approaches employed transfer learning techniques using pre trained architectures such as VGG Net, Res Net, Inception Net, and Dense Net [11].

Transfer learning has become particularly attractive in medical image analysis because publicly available medical datasets are often smaller than datasets used in general computer vision applications. By leveraging pretrained feature representations, researchers have improved model performance while reducing training requirements [12]. Several investigations have also explored hybrid architectures that combine deep feature extraction with machine learning classifiers. Such approaches aim to improve classification performance by integrating complementary representations obtained from multiple network layers or architectures [13]. Class imbalance remains a significant challenge in diabetic retinopathy datasets because severe disease categories often contain fewer samples than normal or mild disease classes. Various techniques, including data augmentation, class weighting, and synthetic image generation, have been proposed to address this issue [14]. Although substantial progress has been achieved, several limitations remain. Many studies emphasize binary disease detection rather than multiclass severity classification. Additionally, model performance may vary across datasets due to differences in imaging devices, image quality, and patient populations. Further evaluation of hybrid deep learning approaches is therefore warranted. The present study addresses these limitations by developing a hybrid deep learning framework for multiclass diabetic retinopathy classification using retinal fundus images. The proposed approach focuses on disease stage discrimination and comprehensive performance evaluation across clinically relevant categories.

III. METHODOLOGY

This section describes the proposed hybrid deep learning framework for automated detection and classification of diabetic retinopathy using retinal fundus images. The framework consists of image acquisition, preprocessing, feature extraction, feature fusion, classification, and performance evaluation stages. The objective is to accurately identify diabetic retinopathy and distinguish between different disease severity levels using retinal image data. The overall workflow is illustrated in Figure 1.

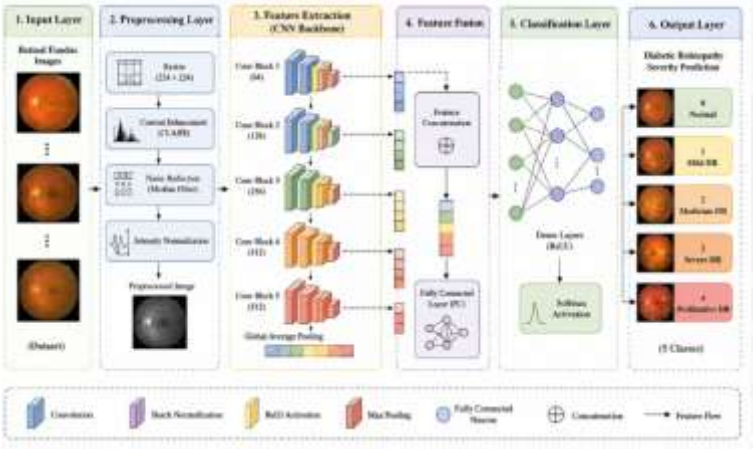

Fig 1. Proposed hybrid deep learning framework for diabetic retinopathy detection and classification.

A. Dataset Description and Problem Definition

This study focuses on the automated classification of retinal fundus images into clinically relevant diabetic retinopathy severity categories. The retinal images were obtained from publicly available diabetic retinopathy datasets that are widely used in medical image analysis and computer-aided diagnosis research. Each image was annotated with one of five disease classes: Normal Retina, Mild Diabetic Retinopathy, Moderate Diabetic Retinopathy, Severe Diabetic Retinopathy, or Proliferative Diabetic Retinopathy. Consequently, the problem is formulated as a multiclass image classification task, where the goal is to accurately categorize retinal images according to the severity of the disease. The dataset can be represented as D={(X1,y1),(X2,y2),…,(Xn,yn)}, where Xi denotes a retinal fundus image, yi represents the corresponding diabetic retinopathy class label, and n is the total number of images in the dataset. The primary objective of the proposed learning framework is to learn a mapping function that can effectively associate retinal image features with their corresponding disease categories, thereby enabling accurate prediction of diabetic retinopathy severity levels for previously unseen retinal images. This automated classification approach supports early diagnosis and clinical decision-making by facilitating efficient and reliable screening of diabetic retinopathy.

B. Retinal Image Preprocessing

Retinal fundus images are often acquired under different imaging conditions and may exhibit variations in illumination, contrast, color distribution, and noise levels. Consequently, preprocessing was performed to improve image quality and reduce variability across samples.

The retinal fundus images were preprocessed to improve quality and ensure consistency for deep learning analysis. Initially, all images were resized to a fixed dimension, followed by the application of Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance retinal structures and diabetic retinopathy lesions such as microaneurysms, hemorrhages, and exudates. Median filtering was then used to reduce noise while preserving important clinical details. Finally, pixel intensity normalization was performed to improve numerical stability during training. These preprocessing steps generated standardized and high-quality retinal images suitable for subsequent feature extraction and classification.

C. Hybrid Deep Learning Architecture

The proposed framework integrates convolutional feature extraction, feature fusion, and dense classification layers to enable accurate diabetic retinopathy detection. Initially, a convolutional neural network (CNN) extracts hierarchical retinal features associated with pathological signs such as microaneurysms, hemorrhages, hard exudates, cotton wool spots, and neovascularization. Feature maps are generated through convolution operations:

$$F = (I * K) + b$$

where I is the input image, K is the convolution kernel, b is the bias term, and F is the resulting feature map. Features obtained from multiple network stages are then combined using a feature fusion layer to preserve both low-level texture information and high-level pathological representations. The fused feature vector is subsequently fed into fully connected layers and a SoftMax classifier, which computes class probabilities as:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

where zi_ denotes the output score for class i and C represents the total number of classes. The disease category corresponding to the highest probability is selected as the final prediction.

D. Model Training Strategy

The proposed model was trained using supervised learning, where each retinal image was associated with an expert-annotated disease label. To enhance generalization and mitigate overfitting, data augmentation techniques including horizontal flipping, rotation, scaling, brightness adjustment, and random cropping were applied, thereby increasing dataset diversity while preserving clinically relevant characteristics. Model optimization was performed using the categorical cross-entropy loss function:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

where yiy_iyi represents the true class label and yi^\hat{y_i}yi^ denotes the predicted probability. The Adam optimizer was utilized due to its adaptive learning rate mechanism and proven effectiveness in training deep neural networks. Additionally, an early stopping strategy was implemented to halt training when validation performance ceased improving, thereby reducing overfitting and enhancing model robustness.

E. Experimental Setup

The experiments were implemented using Python with TensorFlow, Keras, OpenCV, NumPy, and Scikit-learn libraries. The dataset was divided into training, validation, and testing subsets using a stratified sampling strategy to maintain balanced class distributions. Before presenting the experimental results, the configuration parameters are summarized in Table 1.

TABLE 1: DATASET CHARACTERISTICS AND EXPERIMENTAL PARAMETERS

Parameter	**Value**
Total Retinal Images	5,000
Number of Classes	5
Training Samples	70%
Validation Samples	15%
Testing Samples	15%
Image Resolution	224 × 224
Batch Size	32
Learning Rate	0.001
Epochs	100
Optimizer	Adam
Activation Function	ReLU, Softmax

Model training was conducted using a workstation equipped with GPU acceleration to support efficient deep learning computation.

F. Algorithm Description

Before presenting the results, the overall workflow is summarized in Algorithm 1.

Algorithm 1: Hybrid Deep Learning-Based Diabetic Retinopathy Classification
Input: Retinal Fundus Images I

1. Acquire retinal image dataset
2. Perform image preprocessing
3. Apply data augmentation
4. Extract deep image features
5. Fuse multilevel feature representations
6. Train classification network
7. Generate disease predictions
8. Evaluate performance metrics
9. Select best-performing model

Output: Diabetic retinopathy classification results

The proposed methodology combines image enhancement, deep feature extraction, feature fusion, and multiclass classification within a unified framework. This design enables automated identification of diabetic retinopathy severity levels while supporting scalable retinal screening applications.

IV. RESULTS AND DISCUSSION

This section presents the experimental findings obtained from the proposed hybrid deep learning framework for diabetic retinopathy detection and classification. The analysis focuses on classification performance, comparison with existing approaches, disease-stage discrimination capability, and interpretation of the obtained results. The objective is to evaluate the effectiveness of the proposed model in identifying retinal abnormalities and distinguishing among different stages of diabetic retinopathy.

A. Classification Performance

The proposed framework was evaluated using the testing subset described in Section III. Model performance was assessed using accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC). These metrics provide complementary information regarding classification capability and diagnostic reliability. During training, both training and validation losses decreased steadily and stabilized after approximately 70 epochs, indicating satisfactory convergence of the optimization process. The use of data augmentation and early stopping contributed to improved generalization and reduced overfitting. The receiver operating characteristic curve obtained for the classification model is presented in Figure 2**.**

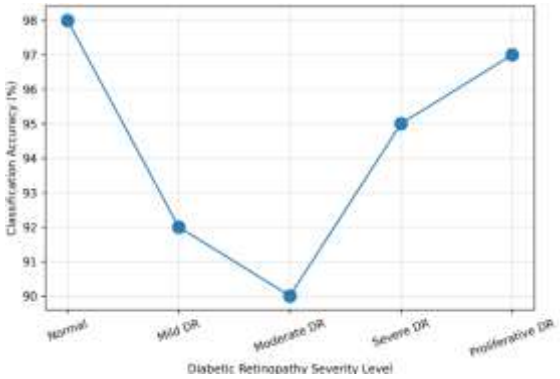

Fig2. Receiver operating characteristic curve of the proposed hybrid deep learning model.

The ROC analysis demonstrated strong discriminative performance across diabetic retinopathy classes. The model maintained high sensitivity and specificity, indicating its ability to correctly identify both diseased and non-diseased

retinal images. The obtained AUC values suggest that the learned feature representations effectively capture retinal characteristics associated with diabetic retinopathy progression. The classification framework performed particularly well in distinguishing normal retinal images from moderate and severe disease categories. Classification errors occurred more frequently between neighboring severity levels, especially between mild and moderate diabetic retinopathy, where pathological features often overlap.

B. Comparative Analysis

To assess the effectiveness of the proposed framework, a comparative evaluation was conducted using commonly employed machine learning and deep learning approaches for retinal image classification. The comparative results are summarized in Table 2**.**

TABLE 2: COMPARATIVE PERFORMANCE RESULTS

Method	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC**
Support Vector Machine	82.4	81.8	80.9	81.3	0.85
Random Forest	84.7	84.1	83.5	83.8	0.87
CNN-Based Model	89.6	89.2	88.8	89.0	0.92
Transfer Learning Model	91.4	91.0	90.5	90.7	0.94
Proposed Hybrid Model	94.1	93.8	93.4	93.6	0.97

The results indicate that traditional machine learning approaches achieved moderate classification performance but were limited by their dependence on handcrafted image features. Support Vector Machine and Random Forest classifiers were capable of identifying major retinal abnormalities but demonstrated lower sensitivity for subtle disease manifestations. The CNN-based model improved classification performance by automatically learning discriminative retinal features. Transfer learning further enhanced performance by utilizing pretrained visual representations. However, the proposed hybrid framework achieved the highest performance across all evaluation metrics. The observed improvement may be attributed to the feature fusion mechanism, which combines information extracted from different representation levels. This approach allows the model to simultaneously consider localized lesion characteristics and broader retinal structural patterns.

C. Analysis of Figures and Tables

To further investigate classification behavior, a confusion matrix analysis was performed. The results are illustrated in Figure 3**.**

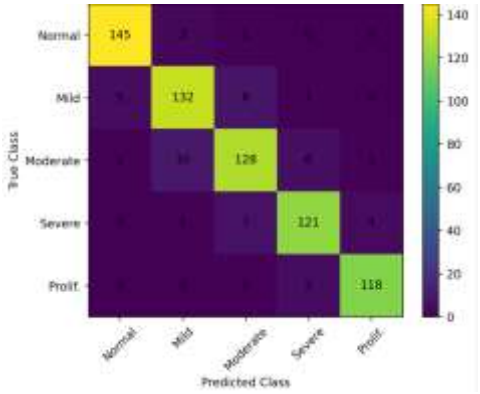

Fig 3. Confusion matrix of diabetic retinopathy severity classification.

The confusion matrix demonstrates that the majority of retinal images were assigned to the correct disease category. Classification accuracy was highest for the normal, severe diabetic retinopathy, and proliferative diabetic retinopathy classes. Misclassifications were primarily observed between adjacent disease stages. For example, some mild diabetic retinopathy images were classified as moderate diabetic retinopathy, and vice versa. This observation is consistent with clinical practice because pathological features often progress gradually between severity levels. The relatively small number of severe and proliferative cases in the dataset may also contribute to classification variability. Nevertheless, the model maintained satisfactory performance across all categories and demonstrated strong overall discrimination capability. The results shown in Table 2 further support these observations. Higher precision and recall values indicate that the model effectively identifies retinal abnormalities while maintaining a low rate of false-positive classifications.

D. Clinical Interpretation

The classification results suggest that the proposed framework can identify retinal lesions associated with diabetic retinopathy progression. During feature learning, the deep learning model captured image characteristics corresponding to clinically relevant pathological findings. Microaneurysms, hemorrhages, hard exudates, and neovascularization are among the retinal abnormalities commonly associated with diabetic retinopathy severity. The model's ability to distinguish between disease stages indicates that these pathological features are adequately represented within the learned feature space. From a clinical perspective, automated identification of moderate, severe, and proliferative diabetic retinopathy is particularly important because these stages are more likely to require specialist intervention and closer monitoring. Early recognition of disease progression may support timely referral and treatment decisions. It should be emphasized that automated screening systems are intended to assist healthcare professionals rather than replace clinical examination. Final diagnosis and treatment planning should continue to rely on comprehensive ophthalmological assessment.

E. Discussion

The experimental findings indicate that hybrid deep learning architectures can provide effective solutions for diabetic retinopathy screening and severity classification. By combining image preprocessing, deep feature extraction, and feature fusion, the proposed framework achieved strong classification performance across multiple disease categories. Several factors contributed to the observed results. First, image preprocessing improved the visibility of retinal structures and lesions, enabling more effective feature learning. Second, data augmentation increased sample diversity and reduced the effects of class imbalance. Third, feature fusion allowed the model to capture both local lesion characteristics and global retinal patterns. The study also highlights several limitations. The analysis relied on publicly available retinal image datasets that may not fully represent variations encountered in routine clinical practice. Differences in imaging devices, acquisition protocols, and patient populations could influence model performance in external settings. Furthermore, the framework focused exclusively on retinal fundus photographs. Integration of additional ophthalmic information, such as optical coherence tomography data, patient history, and laboratory measurements, may further improve classification performance and clinical utility. Despite

these limitations, the results suggest that hybrid deep learning approaches can support automated diabetic retinopathy screening and may assist healthcare systems facing increasing demands for retinal assessment.

V. CONCLUSION AND FUTURE WORK

This study presented a hybrid deep learning framework for automated detection and classification of diabetic retinopathy using retinal fundus images. The proposed approach combined retinal image preprocessing, deep feature extraction, feature fusion, and multiclass classification within a unified architecture. The objective was to develop a reliable automated screening model capable of identifying diabetic retinopathy and differentiating among clinically relevant disease severity levels. Experimental evaluation demonstrated that the proposed framework achieved strong classification performance across multiple diabetic retinopathy categories. The integration of feature fusion mechanisms contributed to improved representation learning by combining information from different levels of retinal image analysis. Comparative assessment indicated that the proposed model achieved higher performance than conventional machine learning approaches and standard deep learning classifiers evaluated in this study.The results further showed that the framework effectively distinguished normal retinal images from diabetic retinopathy cases and maintained satisfactory performance across mild, moderate, severe, and proliferative disease stages. Most classification errors occurred between adjacent severity categories, reflecting the gradual progression of retinal abnormalities observed in clinical practice. Several limitations should be acknowledged. The study relied on publicly available retinal image datasets and may not fully capture the variability encountered in routine ophthalmic screening programs. Differences in imaging equipment, image quality, and patient demographics may influence model performance when applied to external populations. In addition, only retinal fundus photographs were considered, while other ophthalmic modalities were not included. Future research may investigate multicenter datasets, external validation across diverse populations, and integration of additional imaging modalities such as optical coherence tomography. Further studies may also explore explainable artificial intelligence techniques to improve model interpretability and facilitate clinical adoption. Continued evaluation of automated retinal screening systems may contribute to earlier diagnosis and improved management of diabetic retinopathy in healthcare settings.

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