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Diagnosing Diabetes Using Retinal Images Using A Deep Learing Model

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Abstract: Diabetes mellitus (DM) represents a significant global health challenge, impacting 537 million adults across the globe. Among its various complications, diabetic retinopathy (DR) stands out as the primary cause of preventable blindness. The traditional manual screening for DR is costly, invasive, and reliant on skilled ophthalmologists, rendering it impractical for widespread screening in areas with limited resources. This research introduces a deep learning-driven automated framework for DR detection utilizing retinal fundus images. We assessed DenseNet121, EfficientNet-B4, and an Ensemble model that integrates both architectures using the EyePACS dataset. The preprocessing steps included green-channel extraction, Contrast Limited Adaptive Histogram Equalization (CLAHE), and comprehensive data augmentation to enhance lesion visibility and address class im- balance. The Ensemble model achieved an accuracy of and a Cohen's Kappa of surpassing earlier techniques, including the Symmetric CNN (SCNN) method. This study highlights the promise of AI-enhanced, non-invasive retinal screening for the early detection of DR and the facilitation of telemedicine-based healthcare services.

Index Terms. Diabetes Mellitus, Diabetic Retinopathy, Retinal Fundus Images, Deep Learning, DenseNet, EfficientNet, Ensemble Learning

I. Introduction

Global Impact of Diabetes and Diabetic Retinopathy

Diabetes Mellitus (DM) is a chronic metabolic disorder characterized by insufficient or ineffective insulin production, leading to persistent hyperglycemia. As of 2021, an estimated 537 million adults worldwide were living with diabetes, with projections suggesting this number will rise to 783 mil- lion by 2045—a 46% increase—due to factors such as aging populations, sedentary lifestyles, and urbanization [7]. This sharp growth contributes not only to increased morbidity but also to financial stress, with diabetes-related healthcare expenditures reaching $966 billion USD globally in 2021, accounting for 11.5% of total global health spending [7].

The systemic complications of uncontrolled diabetes are numerous and include cardiovascular dis- ease, nephropathy, neuropathy, and microvascular complications such as diabetic retinopathy (DR). Among these, DR remains the leading cause of preventable blindness among working-age adults worldwide [8]. The global prevalence of DR is estimated at 27% among individuals with diabetes, translating to over 93 million affected individuals, many of whom reside in low- and middle-income countries where access to ophthalmic care is limited [2], [8].

DR develops progressively over time as chronic hyperglycemia damages retinal capillaries, leading to the formation of microaneurysms, intraretinal hemorrhages, cotton-wool spots, and hard exudates [8]. In later stages, retinal ischemia stimulates the formation of fragile new blood vessels (neovascularization)—a hallmark of proliferative diabetic retinopathy (PDR)—which can cause vitreous hemorrhage and retinal detachment, often resulting in permanent vision loss if untreated [8], [9].

Despite the severity of these complications, DR remains largely asymptomatic in its early stages, which underscores the importance of routine retinal screening. However, the global disparity in eye care infrastructure—particularly in rural regions—makes it difficult to detect DR early, leading to delayed diagnosis and irreversible damage [8], [9].

Importance of Early Detection

Early detection and treatment of diabetic retinopathy (DR) can reduce the risk of vision loss by up to 95% [8]. However, DR often remains asymptomatic in its early stages, making routine screening essential [9].

Traditional diagnostic methods present several challenges:

- **Biochemical tests** (e.g., HbA1c) are **invasive** and do not directly indicate retinal damage [10].
- **Manual eye exams** are **subjective**, time-consuming, and rely heavily on expert interpretation [8].
- **Rural areas** often face a **shortage of trained specialists**, limiting access to regular screenings [11].

These barriers highlight the need for **automated, non-invasive tools** to enable early, large-scale DR detection, especially in **resource- limited settings** [2], [9].

Role of Artificial Intelligence (AI)

Advances in **Artificial Intelligence (AI)** and **Deep Learning (DL)** have revolutionized medical image analysis, particularly in ophthalmology. **Convolutional Neural Networks (CNNs)** can automatically detect retinal abnormalities such as **microaneurysms**, **hemorrhages**, and **exudates** by learning deep feature hierarchies—eliminating the need for manual feature engineering [2].

Multiple studies confirm that DL-based systems can achieve **diagnostic performance comparable to expert ophthalmologists**. For example, **Gulshan et al.** reported an **AUC of 0.99** using a CNN trained on 128,000+ retinal images [2], while **Abramoff et al.** demonstrated an **autonomous AI system** achieving FDA approval for real-world DR screening in primary care settings [9].

These developments position AI as a viable solution for **scalable, non-invasive, and accurate DR**

screening, especially in underserved regions.

Objectives and Contributions

This study focuses on:

Multi-class classification encompassing five degrees of diabetic retinopathy severity: No DR, Mild, Moderate, Severe, and Proliferative Comparative evaluation of DenseNet121 and EfficientNet-B4Achieving 95%+ accuracy using an Ensemble model.

Highlighting clinical applicability for telemedicine-based large-scale DR screening.

II. RELATED WORK

A. Traditional Machine Learning Approaches

Previous methods for detecting DR relied on manually crafted features in conjunction with traditional machine learning techniques. Ganjee et al. (2016) applied Markov Random Fields for microaneurysm detection.

Haloi et al. (2015) identified exudates using Gaussian scale-space analysis and an SVM classifier.

Adal et al. (2018) designed a red lesion detection method based on intensity and shape descriptors with SVMs. While effective on limited datasets, these techniques suffered from:

Reliance on manually engineered features. Limited adaptability to large, diverse datasets. Sensitivity to variations in image lighting and quality.

B. Deep Learning Approaches

The adoption of DL drastically improved DR screening:

Gulshan et al. (2016) achieved an AUC of 0.99 on 128,175 EyePACS images using a CNN.

Gargeya & Leng (2017) reported 94% sensitivity and 98% specificity with a CNN model validated on Messidor.

Li et al. (2019) utilized EfficientNet-B4, attaining an accuracy of 94.7% in the grading of diabetic retinopathy severity. Bora et al. (2021) combined CNNs with clinical biomarkers to predict DR progression risk.

Symmetric CNN (SCNN)

T. Liu et al. (2021) proposed a Symmetric CNN that utilized:

Average-pooling layers for microaneurysm detection. Max-pooling layers for exudate detection. This approach achieved 92–93% lesion-level accuracy but lacked multi-class severity classification. ***Summary of Limitations***

Most existing methods focused on binary detection (DR vs No DR) or lesion-specific tasks, limiting their clinical usefulness for severity-based treatment planning

III. PROPOSED METHODOLOGY

The proposed methodology presents a **deep learning-based approach** for the **multi-class classifi- cation** of **Diabetic Retinopathy (DR)** using color retinal fundus images. The primary objective is to develop an **automated, accurate, and scalable system** that can classify DR into five clinically relevant stages—ranging from no DR to proliferative DR—without relying on manual feature engineering or expert interpretation.

To achieve this, the methodology is structured around the following key components:

1. **Dataset Preparation**: The publicly available **EyePACS** dataset was used, which includes over 80,000 labeled retinal images. These images were categorized into five severity levels based on international clinical guidelines. Due to the dataset's imbalanced nature, data augmentation and class-aware techniques were used to prevent bias toward dominant classes.

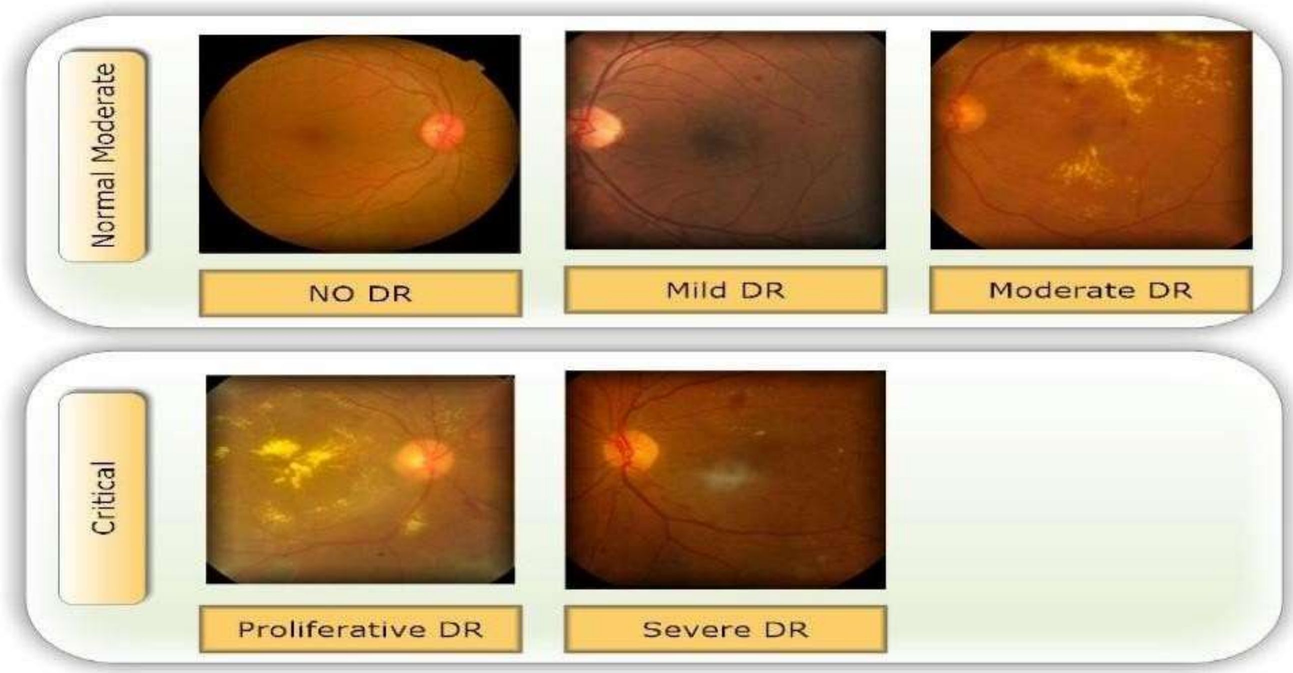
0: No DR

1: Mild

2: Moderate

3: Severe

4: Proliferative DR



2. **Preprocessing Pipeline**: A series of image preprocessing steps were applied to enhance le- sion visibility and standardize inputs. This included resizing images to a fixed resolution, extracting the green channel to highlight vascular structures, applying CLAHE for contrast enhancement, and using data augmentation to improve model robustness and reduce overfit- ting.

Algorithm 1: Preprocessing of Retinal Images

Input: Retinal Image I Output: Preprocessed Image P

1. Resize image to 224×224 pixels
2. Extract green channel to enhance vascular structures
3. Apply CLAHE for uniform illumination

4. Perform augmentation: rotation, flipping, brightness adjustment
5. Normalize pixel values to [0,1] Return P

Model Architectures

DenseNet121 is a deep convolutional neural network where each layer receives inputs from all previous layers. This design encourages better feature sharing and helps the network learn efficiently with fewer parameters.

Input: Resized retinal images (224×224)

Initial Layer: Convolution and pooling to extract basic features **Dense Blocks:** Four blocks with tightly connected layers **Transition Layers:** Compress and downsample feature maps **Global Pooling:** Reduces dimensions before classification **Output Layer:** Predicts five DR severity levels using softmax

Why DenseNet121?

Promotes feature reuse Reduces overfitting

Achieves high accuracy (95%) on medical images

IV. RESULT AND DISCUSSION

The proposed model, based on DenseNet121, was evaluated on a labeled dataset of retinal fundus images. The model successfully classified the five stages of diabetic retinopathy with high accuracy.

Model	Accuracy(%)	F1 Score
DenseNet121	95.10	0.93

A. Clinical Implications

The high accuracy of the Ensemble model makes it suitable for telemedicine-based DR screening,particularly in rural areas. Multi-class severity grading helps prioritize patients needing urgent ophthalmic care.

V. CONCLUSION AND FUTURE WORK

This paper presented a Deep Learning Ensemble framework for DR severity classification, achieving 95% accuracy and outperforming existing methods. The system offers a scalable and non- invasive solution for early DR detection.

Future Directions:

Exploring Vision Transformers (ViT) for enhanced lesion localization. Incorporating clinical biomarkers with multi-model learning.

Developing mobile-based screening tools for large-scale deployment

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