REPORT- AI-driven Remote Fundus Imaging and Tele-Ophthalmology

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1. Introduction

The Challenge: A Leading Cause of Preventable Blindness

Diabetic Retinopathy (DR) is one of the main reasons for preventable blindness across the world. The key to saving a person's sight is early detection. The basic method for diagnosis involves manually grading specialized eye scans i.e fundus images. This process is not only slow but also requires the keen eye of an ophthalmologist who is often not available in remote or underserved communities. This gap in healthcare access creates a need for a system that can analyze these images and support doctors through tele-ophthalmology and that is what we are trying to address the SDG 4.

Our work is driven by a clear motivation: early medical intervention can prevent the majority of blindness cases that result from DR. By using AI, we can create solutions that make timely diagnosis which is accessible to everyone, regardless of their location, overcoming the hurdles of time and the need for on-site specialists.

Our Goals

- Classify Diabetic Retinopathy from fundus images
- Implement CLAHE preprocessing for enhanced image quality
- Build and compare multiple deep learning architectures

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2. Building on Previous Work

A Look at Existing Research

The project is built upon a strong foundation of prior research in Diabetic Retinopathy detection. Significant progress has been made over the years, from clinical validation of deep learning models to the pre-trained networks for retinal imaging.

Author & Year	Approach / Model	Key Contribution
Gulshan et al., 2016	Deep CNN (Inception-v3)	Large-scale DR detection

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Pratt et al., 2018	Custom CNN (5 conv layers)	An end-to-end pipeline for analyzing the fundus images
Lam et al., 2018	Transfer Learning (VGG/ResNet)	Adapting powerful pre-trained models for the retinal images
Srinivasan et al., 2020	Hybrid CNN-SVM	Combining both deep learning features with classic machine learning
Our Proposed Work (2024)	**Multi-Branch CNN + Ensemble**	**Fusing DenseNet201 & ResNet50 with explainable AI**

Research Gap

Simpler, single-pathway AI models can sometimes fail to capture the full range of complex features in a retinal scan. We also noticed limited research into more advanced multi-branch or hybrid models designed specifically for DR. Furthermore, many existing models operate as "black boxes," making it difficult for doctors to trust their conclusions. Finally, image enhancement techniques like CLAHE have not been fully optimized within deep learning pipelines for fundus images. Our work aims to fill these gaps.

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3. Our Approach

Preparing the Data

Our foundation was a dataset of fundus images, already categorized into five severity classes of DR. To ensure they were ready for our models, we firstly resized every image to a standard 224×224 pixels. Then we applied a powerful contrast-enhancement technique i.e Contrast Limited Adaptive Histogram Equalization (CLAHE), to make subtle features like blood vessels and lesions more visible. To properly train and test our system, we divided the dataset into following manner 70% for training, 15% for validation during training, and the final 15% for testing. We also balanced the dataset to prevent the model from becoming biased toward the more common classes.

The AI Architecture Structure

We developed and compared two core models:

- **Multi-Branch CNN:** Our advanced model, which combines the strengths of both architectures i.e DenseNet201 and ResNet50. By fusing features from both the model can have a more detailed understanding of the images.

- **2D CNN Baseline:** A more conventional, straightforward model with 3 convolutional blocks. This served as our baseline to measure just how much of an improvement the multi-branch approach offered.

Both models were designed to output a final prediction across the five severity levels of DR.

Training and Strategy

To train the models effectively, we used the Adam optimizer and a dynamic learning rate that adjusted itself based on performance. We also implemented "early stopping" so that there is no overfitting issue. To combine the strengths of both architectures, we created an ensemble model. This final model makes its prediction by taking a weighted vote from the other two, giving 70% of the weight to the superior Multi-Branch CNN and 30% to the 2D CNN to incorporate its complementary features.

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4. What We Discovered: Results and Analysis

Performance on the Test Set

When we put our models to the test, the results were definitive. The Multi-Branch CNN was the clear standout by an outstanding test accuracy of 93.19%. The ensemble model also performed exceptionally well at 92.29%, while our baseline 2D CNN achieved a respectable 83.15%. During the training process, we observed that the multi-branch model learned steadily and consistently, whereas the baseline model's performance plateaued much earlier and not that accurate.

A Deeper Look at the Results

The Multi-Branch CNN was not just more accurate overall; it was exceptionally good at identifying the specific severity of the disease, which is critical for clinical use. In contrast, the baseline 2D CNN struggled to tell the difference between moderate and severe stages of DR.

Also, the Multi-Branch CNN provided balanced predictions across all classes. The baseline model, however, showed a strong bias toward predicting "no disease," which is a dangerous flaw as it could lead to missing actual cases of retinopathy. Because our ensemble model was heavily weighted toward the multi-branch architecture, it successfully retained this strong disease-detection capability.

Our Key Findings

This experiment led to several important conclusions:

- The advanced multi-branch architecture significantly outperformed a standard design by a margin of about 10% in accuracy.
- Using CLAHE to preprocess the images substantially improved feature visibility and, in turn, model performance.
- The combination of transfer learning with a multi-branch design is a highly effective strategy for this kind of medical image analysis.
- By integrating saliency maps, we were able to provide a window into how the model was making its decisions, a crucial step toward clinical trust and interpretability.

5. Conclusion: A Step Forward for AI in Ophthalmology

The multi-branch CNN architecture, with its remarkable 93.19% test accuracy, has proven to be a great approach for classifying Diabetic Retinopathy compared to conventional models. It demonstrated stable, effective learning and, through the use of saliency maps, offered a transparent look into its decision-making process.

This research lays a robust foundation for the future of automated fundus image analysis. The multi-branch design has shown itself to be particularly effective for the complex task of identifying retinal diseases. We believe this work represents a significant contribution to the field of AI-powered ophthalmology and holds the potential to make a transformative impact on healthcare accessibility for patients all over the world.

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