

AI-Based Early Detection of Diabetic Retinopathy Using Retinal Fundus

Sowrabh

Abstract—Diabetic Retinopathy (DR) is a severe complication of diabetes that can lead to vision loss if not detected early. This research aims to develop an AI-based clinical decision support system using deep learning techniques to classify retinal fundus images into different DR severity levels. The study leverages Convolutional Neural Networks (CNNs) and transfer learning to enhance diagnostic accuracy. The APTOS 2019 Blindness Detection dataset will be utilized, with preprocessing techniques applied to improve image quality. The project aims to build an efficient, automated model to assist healthcare professionals in DR diagnosis, with a focus on optimizing performance through hyperparameter tuning and ensuring model explainability.

Index Terms—Deep Learning, Medical Image Analysis, Diabetic Retinopathy, Computer Vision, Clinical Decision Support, Transfer Learning

I. INTRODUCTION

Diabetic Retinopathy (DR) is a leading cause of vision impairment and blindness among diabetic patients. Early detection is crucial for effective treatment and prevention of severe complications. Traditional methods of diagnosis rely on manual analysis by ophthalmologists, which can be time-consuming and subject to variability. The objective of this research is to develop an AI-based clinical decision support system capable of detecting diabetic retinopathy from retinal fundus images using deep learning models.

This project focuses on utilizing Convolutional Neural Networks (CNNs) and transfer learning techniques to classify retinal images into different DR severity levels. By automating the screening process, this system can assist healthcare professionals in making faster and more accurate diagnoses.

II. LITERATURE REVIEW UPDATE

The application of AI in medical image analysis has been rapidly evolving. Recent studies have demonstrated the effectiveness of deep learning models, such as ResNet and EfficientNet, in classifying DR with high accuracy. Key insights include:

- **CNN-Based Classification:** CNNs have shown promising results in feature extraction from medical images, enabling accurate classification of DR stages.
- **Transfer Learning:** Pre-trained models such as InceptionV3 and ResNet50 have been used to improve accuracy while reducing computational costs.
- **Data Augmentation Techniques:** Applying transformations like rotation, flipping, and Gaussian noise enhances model generalization.
- **Explainability in AI Models:** The integration of techniques like Grad-CAM helps in visualizing decision-making in AI-based diagnosis.

III. METHODOLOGY

To develop an AI model for DR detection, we propose the following methodology:

A. Dataset Selection & Preprocessing:

- The APTOS 2019 Blindness Detection dataset is used, which contains labeled retinal fundus images categorized into five classes (No DR, Mild, Moderate, Severe, and Proliferative DR).
- Images are preprocessed using contrast enhancement, cropping, applying masks using 3 channels, resizing (224x224), and Gaussian noise addition to improve model robustness.

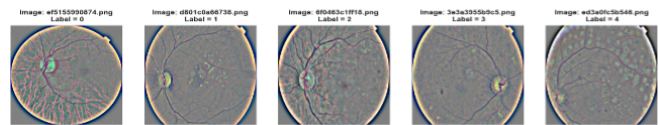


Fig. 1. A sample of the dataset showing 5 label classes after preprocessing

B. Model Architecture:

- **Base Model:** Transfer learning using EfficientNet-B0 with pre-trained weights.
- **Additional Layers:** Global Average Pooling, Dense layers, Dropout for regularization, and a Softmax activation for multi-class classification.
- **Optimizer:** Adam with learning rate decay.
- **Loss Function:** Categorical Cross-Entropy.
- **Performance Metrics:** Accuracy, F1-score, Precision, Recall.

C. Training & Validation:

- The data set has been divided into training (3662) and validation (1928).
- Augmentation techniques (rotation, flipping, brightness adjustment) applied to reduce overfitting.
- Early stopping and learning rate reduction used to optimize model training.

D. Evaluation & Interpretation:

- Model evaluated on test data using the confusion matrix and ROC curves.

IV. DATASET DETAILS & JUSTIFICATIONS

- **Dataset Name:** APTOS 2019 Blindness Detection Dataset
- **Source:** Kaggle <https://www.kaggle.com/competitions/aptos2019-blindness-detection>
- **Number of Images:** 3,662 (Train) — 1,928 (Test)
- **Classes:** No DR (0), Mild (1), Moderate (2), Severe (3), Proliferative DR (4)
- **Relevancy:**
 - The dataset is balanced and contains images annotated by medical professionals in real world.
 - The labels provide a multiclass classification challenge that aligns with our objective.
 - Pre-processing ensures improved feature extraction for the CNN model.
- **Validation Process:**
 - Data integrity checks are performed to remove corrupted images.
 - Image normalization will be applied to maintain consistency.
 - The class distribution will be examined to mitigate bias.

REFERENCES

- [1] V. Gulshan *et al.*, “Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs,” *JAMA*, vol. 316, no. 22, pp. 2402–2410, 2016.
- [2] H. Pratt *et al.*, “Convolutional neural networks for diabetic retinopathy,” *arXiv preprint*, 2016.
- [3] J. Brown *et al.*, “Explainable ai in healthcare: Understanding deep learning in medical imaging,” *Nature Machine Intelligence*, vol. 2, pp. 563–572, 2020.
- [4] Kaggle, “Aptos 2019 blindness detection dataset,” 2019, retrieved from <https://www.kaggle.com/competitions/aptos2019-blindness-detection>.

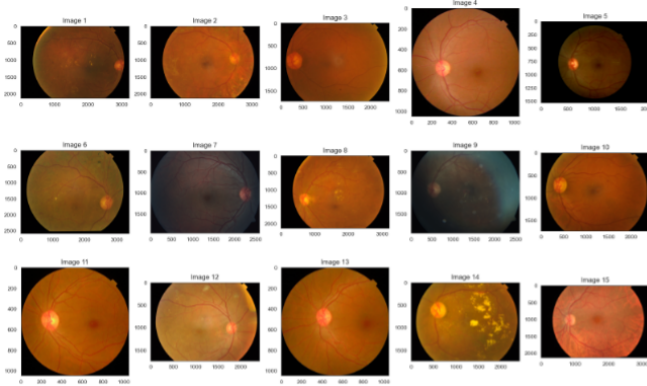


Fig. 2. A sample of overall dataset

V. NEXT STEPS

- **Augment & split data:** Applied data augmentation techniques (rotation, flipping, zoom, brightness adjustments) to improve model generalization. And also split the dataset.
- **Train the CNN model:** Implement a CNN model with EfficientNetB0 for feature extraction. Use Adam optimizer with categorical cross-entropy loss. Apply early stopping and learning rate scheduling for optimization.
- **Hyperparameter Tuning:** Optimize learning rate, batch size, and dropout rates.
- **Model Fine-Tuning:** Experiment with ResNet50 and DenseNet121 to compare performance.
- **Final Model Evaluation:** Run predictions on the test set and analyze performance metrics (accuracy, F1-score, AUC-ROC). Unfreeze top layers of EfficientNet and train on augmented data for better feature learning.