Ensemble of Deep Learning Models for Eye Diseases Classification

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Abstract

This study implements advanced deep learning models to classify eye diseases using computer vision techniques, with an ensemble approach combining bagging and voting for improved accuracy and robustness. Targeting diseases like diabetic retinopathy, glaucoma, and macular degeneration, the model achieves superior performance over single models, addressing challenges like image variability, class imbalance, and multi-disease diagnosis. A Bangladeshi-specific dataset bridges a critical representation gap. The model outperforms others, achieving accuracy of 78.01% that enables reliable early detection to prevent vision loss.

Keywords

Deep learning, Ensemble, CLAHE, Unsharp Masking, Classification, Image pre-processing

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1 Introduction

Our project is about the implementation of advanced deep-learning models to classify eye diseases based on computer vision techniques. The ensemble of deep learning models using bagging and voting for better performance. This approach can perform multi-disease classification. Eye diseases such as diabetic retinopathy, glaucoma, and age-related macular degeneration cause blindness that deep-learning classification models can detect. The single model struggles with accuracy due to image variability, class imbalance, and difficulties in handling multi-disease diagnosis. An ensemble of deep learning models can solve these issues by combining the strengths of multiple models, improving accuracy, robustness, and reliability for better classification of eye diseases. This study focuses on a dataset that specifically represents Bangladeshi ethnicity. This addresses a significant gap, as previous studies have not represented Bangladeshi ethnicity. We apply a comprehensive preprocessing pipeline for enhanced Image Analysis like sharpening edges, adjusting lighting, CLAHE, and Gaussian Blur, applying Color Normalization with Noise Reduction for consistency, and augmentation to enhance dataset diversity and resolve class imbalance. The traditional detection system is time-consuming. This study helps reduce diagnostic errors and early detection of eye disease that prevents vision loss. Deep learning models can learn and identify the features from images which is suitable for early detection and classification.

2 Related works

"DEEP NEURAL NETWORK-BASED ENSEMBLE MODEL FOR EYE-DISEASES DETECTION AND CLASSIFICATION" by A.A. Jeny et al. [3] presents an automated deep learning ensemble model for detecting and classifying eye diseases from fundus images. It uses a CNN-based model with 20 layers, applying techniques like CLAHE and Gaussian filtering for image clarity. Augmentation techniques prevent overfitting during training. The approach integrates three pre-trained models—VGG16, DenseNet201, and ResNet50—and outperforms recent methods on the ODIR dataset. The study addresses challenges in the screening process, aiming to improve detection efficiency in real-world settings.

A.H. Khan et al.[4] in "Spatial Correlation Module for Classification of Multi-Label Ocular Diseases Using Color Fundus Images" introduce a patient-level multi-label ocular disease classification model (PLML_ODs) that uses a spatial correlation network (SCNet) to consider correlations between bilateral eye images. The model leverages DenseNet-169 for feature extraction, SCNet for pixel-by-pixel correlation analysis, and a classifier for the final classification. The PLML_ODs model improves classification performance by integrating bilateral eye information, yielding better results compared to baseline methods. The approach is validated using a publicly available dataset.

S Wang et al. [8] in "An automatic early screening system of eye diseases using UWF fundus images based on deep neural networks" develops an automatic early screening system for multiple eye diseases, using ultra-widefield (UWF) fundus images. The system includes a CNN-based architecture with a feature extractor and classifier. The model uses two feature fusion methods to improve performance. Evaluations on 7,209 UWF fundus images show high accuracy and reliability, validated by ophthalmologists.

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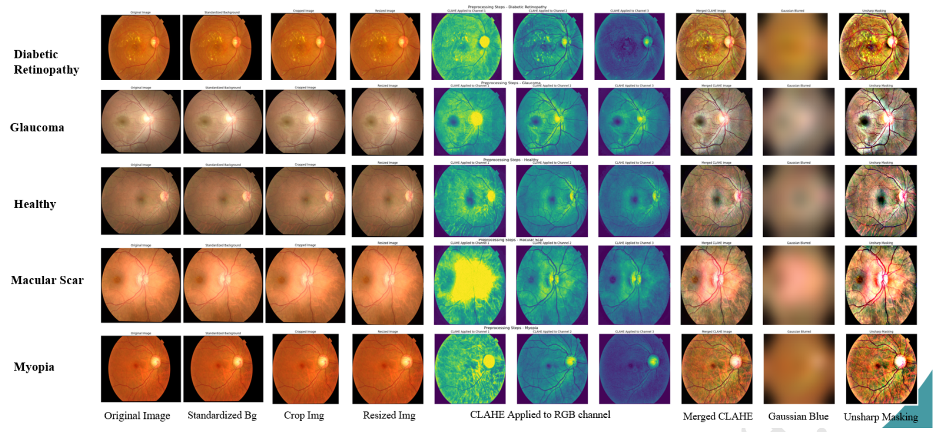

Figure 1: Overview of the preprocessing steps applied to the dataset.

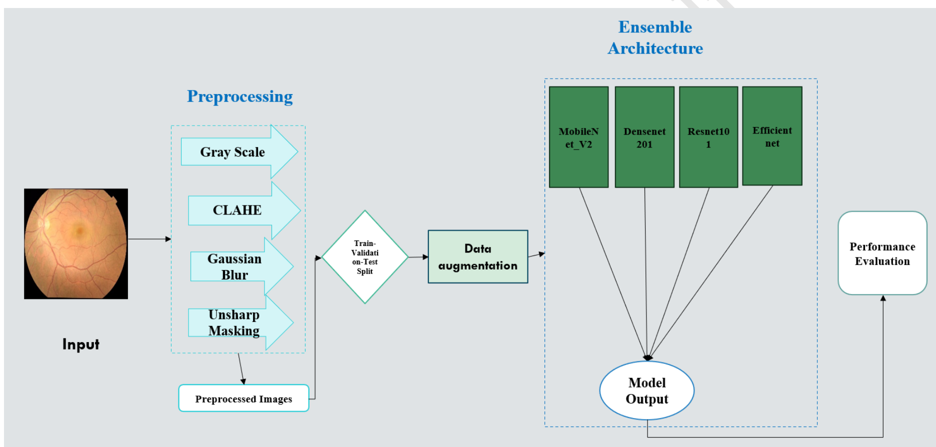

Figure 2: Main flow diagram of the study.

T.R. Athira et al. [2] in "Diabetic Retinopathy Grading From Color Fundus Images: An Autotuned Deep Learning Approach" focuses on an automated system for diagnosing Diabetic Retinopathy (DR) from fundus images. It includes classification into three stages: No DR, Non-Proliferative DR, and Proliferative DR. The proposed method enhances image processing, hyperparameter tuning, and neural network strategies, improving early-stage detection accuracy. When compared with other models like ResNet50, VGG16, and MobileNetV2, the ResNet50-based algorithm outperformed others with a classification accuracy of 94.7% and detection accuracy of 99.8%.

3 Dataset

This study utilizes a dataset [6] of 5,335 color fundus images collected over eight months from Anawara Hamida Eye Hospital and B.N.S.B. Zahurul Haque Eye Hospital in Faridpur, Bangladesh. The dataset comprises ten classes of ocular diseases; however, this study focuses on five key classes due to their relatively higher number of images, ensuring robust model training. These classes include Diabetic Retinopathy(1,509 images), Glaucoma (1,349 images), Healthy(1,024 images), Macular Scar (444 images), and Myopia (500 images). Images were captured using Topcon TRC-50DX and TL-211 fundus cameras, with resolutions standardized to 2,004 × 1,690 pixels. Each image was carefully labeled under expert supervision. This targeted approach addresses the challenges of low data availability in certain classes, enabling reliable detection and classification of prevalent ocular diseases.

4 Preprocessing

The preprocessing shown Figure 1 aim to standardize and enhance the quality of the input data. Initially, the background was standardized, and the fundus region was cropped from the original image. The cropped images were resized to a consistent 224x224 resolution to ensure uniform input dimensions. The images were then split into RGB channels, with Contrast Limited Adaptive Histogram Equalization (CLAHE) applied to each channel to enhance contrast. The channels were merged back together, and Gaussian blur was applied to reduce noise. Unsharp masking was then used to enhance details and improve the clarity of important features.

Model Name	Accuracy	Precision	Recall	F1-Score
Xception	73.54%	0.7541	0.7354	0.7390
Dense Net 121	77.88%	0.7729	0.7688	0.7745
Inception V3	73.13%	0.7301	0.7313	0.7303
Efficient B3	77.59%	0.7743	0.7759	0.7793
Mobile Net V3	77.8%	0.7682	0.7712	0.7712
VGG 19	59.39%	0.5978	0.5939	0.5866
VGG 16	65.98%	0.6570	0.6598	0.6576
Resnet 101	77.42%	0.7726	0.7742	0.7708
Mobile Net V2	77.29%	0.7772	0.7729	0.7717
Dense Net 201	76.92%	0.7652	0.7692	0.7646

Table 1: Performance metrics for different models.

Serial No.	Class Name in Dataset	F1-Score	Precision	Recall
01	Glaucoma	0.9404	0.9404	0.9404
02	Myopia	0.6667	0.6385	0.6587
03	Macular Scar	0.6316	0.6818	0.6034
04	Healthy	0.5814	0.6944	0.5000
05	Diabetic Retinopathy	0.7000	0.7778	0.6364

Table 2: Performance metrics for different classes in the dataset.

Difference	Our Proposed Model (Ensemble Model)	Base Model
Accuracy	78%	76.35%
Precision	78.31%	76.31%
Recall	78.01%	76.35%
F1 Score	78.10%	76.17%

Table 3: Comparison of Model Performance Metrics

Finally, the images were split into training, validation, and testing subsets, which allowed for effective model training and evaluation.

5 Proposed Model

6 Performance of Models

1

7 Performance of Classes

2

8 Confusion Matrix

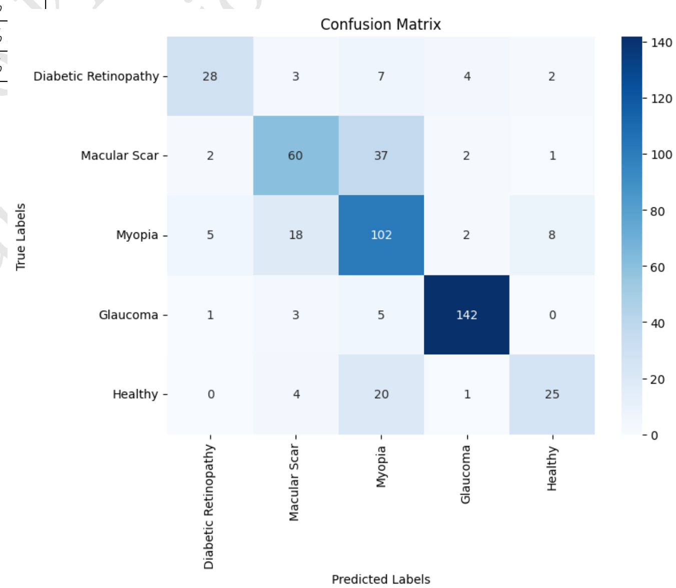

Figure 3: Confusion Matrix showing the performance of the model on the dataset.

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