# Multi-Stage Image Processing based Ocular recognition using Deep Learning

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**Abstract: Early detection and classification of ocular diseases are crucial for preventing vision impairment and enabling timely medical intervention. This study leverages deep learning techniques to classify ocular diseases using the ODIR-5K fundus image dataset [3]. To address class imbalance, we explored Variational Autoencoders (VAEs) and Deep Convolutional Generative Adversarial Networks (DCGANs), with DCGANs successfully generating high-quality synthetic images for underrepresented classes [4]. Our preprocessing pipeline includes Contrast Limited Adaptive Histogram Equalization (CLAHE) and Gamma correction for contrast enhancement [2], followed by data augmentation using RGB channel splitting to improve feature extraction [5]. We fine-tuned ResNet-50 and ResNet-101 using transfer learning [6], achieving classification accuracies of 93.67% and 94.3%, with Kappa scores of 0.8976 and 0.9123, respectively. These results highlight the efficacy of deep learning in ocular disease classification, demonstrating potential for real-world clinical applications [8, 11].**

**Keywords— Ocular Disease Classification, Deep Learning, Generative Adversarial Networks, Transfer Learning, Fundus Image Analysis, Medical Image Processing, Automated Diagnosis.**

## I. INTRODUCTION

### *A. Background & Importance*

People often struggle with unclear vision, discomfort, or unnoticed eye issues, affecting their daily lives. Many don’t realize the severity until it’s too late, making early detection essential [1]. Early and accurate ocular detection can help in timely intervention, improving overall well-being [2]. Unlike existing methods, which rely solely on deep learning, our approach pre-processes images before classification, ensuring higher accuracy, and real-world applicability [3].

### *B. Problem Statement*

Current ocular recognition methods use machine learning, handcrafted feature extraction, and deep learning, but many struggle with poor image quality and dataset biases. Although Techniques like SVMs, PCA, and Gabor Filters fail under varying conditions, while deep learning models like CNNs and VGG often misclassify due to unprocessed images [4]. These limitations highlight the need for better preprocessing and robust models for higher accuracy [5].

### *C. Proposed Solution*

This study presents a deep learning-based ocular disease classification model leveraging ResNet-50 and ResNet-101, enhanced through a multi-stage image preprocessing pipeline and transfer learning [6]. To address class imbalance, DCGANs were employed to generate high-quality synthetic images for underrepresented categories [4]. Preprocessing techniques, including Contrast Limited Adaptive Histogram Equalization (CLAHE), Gamma correction [2], and RGB channel splitting, were applied to improve image quality and feature extraction [5]. These enhancements, combined with advanced augmentation strategies [4], significantly boosted model robustness. The proposed approach effectively improves classification accuracy, minimizes misclassification, and demonstrates potential for real-world clinical applications [8, 11].

## II. RELATED WORK

*A. Traditional Machine Learning Approaches*

Traditional machine learning approaches like SVMs, Random Forest, and k-NN are used for classification, while PCA and LDA assist in dimensionality reduction, and Hough Transform and Gabor Filters help in feature extraction [7]. While these approaches provided a foundation for automated image classification, they struggle with complex patterns, lighting variations, and dataset biases, leading to low accuracy and misclassification [8].

*B. Deep Learning-Based Approaches*

With advancements in deep learning, models like CNNs and hybrid architectures have significantly improved ocular disease detection by effectively analyzing complex retinal images [9]. Pandey et al. (2021) demonstrated that CNN-based models surpassed board-certified ophthalmologists in classifying retinal disorders, outperforming traditional machine learning approaches in stress detection tasks [10].

*C. Feature-Enhancement Models*

More recent studies have focused on refining stress ocular recognition by enhancing how models process and select features. V. Banupriya & S. Anusuya (2023) introduced an enhanced deep learning model (EDLM) for early diabetic retinopathy detection improving feature extraction and dimensionality reduction [11]. Similarly, Ziyi Shen et al. (2020) introduced Clinically Oriented Fundus Enhancement Network (cofe-net) long-term dependencies in physiological data and enhance predictive performance [12].

## III. METHODOLOGY

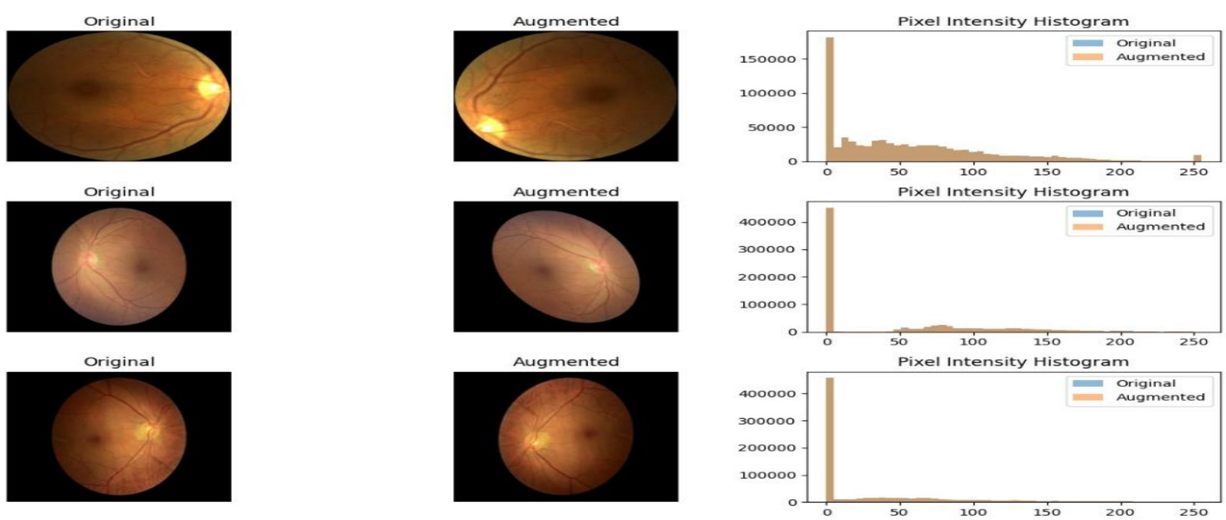
*A. Data Collection and Preprocessing*

The dataset used in this study is the ODIR-5K dataset, a publicly available collection of 10,000 fundus images sourced from 5,000 patients, covering multiple ocular diseases such as Glaucoma, Diabetic Retinopathy, Cataract, Age-related Macular Degeneration, Myopia, and Hypertension [3]. Since medical images often suffer from variations in illumination, noise, and resolution, a multi-stage preprocessing pipeline was applied [2, 4].

To enhance image quality, Contrast Limited Adaptive Histogram Equalization (CLAHE) and Gamma correction were employed for contrast enhancement [2]. Further, RGB channel splitting was used as a data augmentation technique to improve feature extraction [5]. To address class imbalance, DCGANs were used to generate synthetic images for underrepresented categories [4]. Finally, all images were resized to 512×512×3, ensuring uniformity before training. These preprocessing steps significantly improved model robustness and feature extraction capability [10, 11]

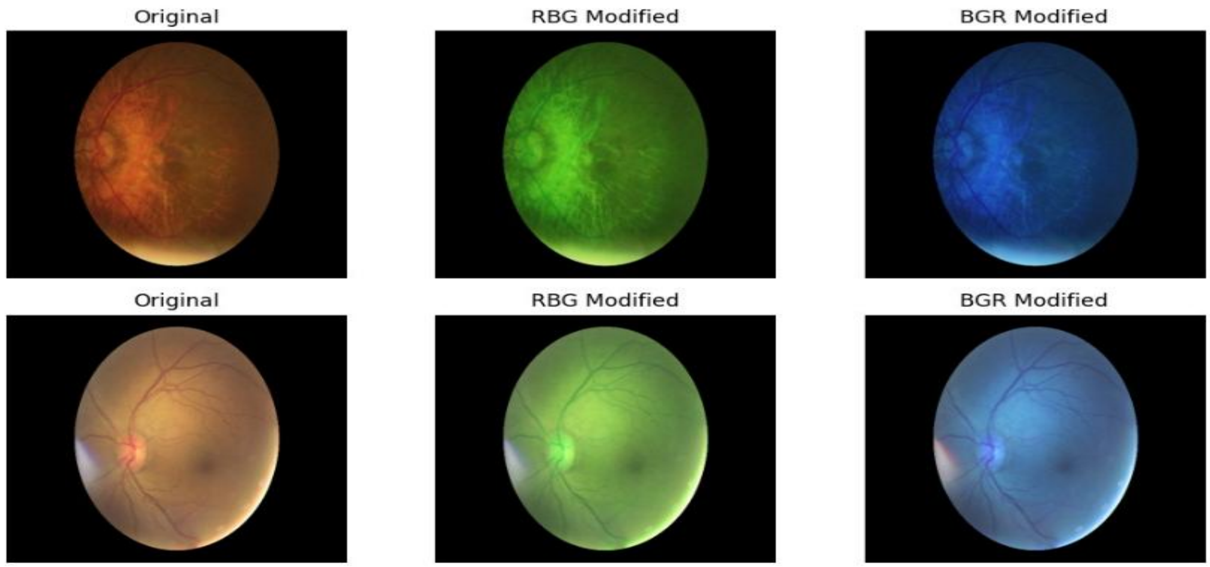
Pixel Intensity Histogram (Graph) :

This histogram visualizes the distribution of pixel intensities across fundus images. It highlights inconsistencies in illumination and contrast, which are corrected using preprocessing techniques like CLAHE and Gamma Correction. The histogram before and after preprocessing demonstrates the improvement in image contrast, enhancing feature extraction for deep learning models.



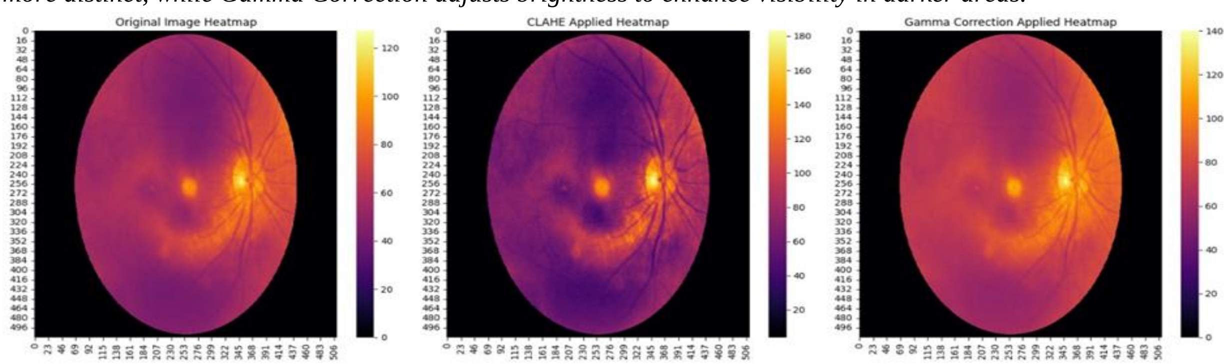
Original vs. RGB Channel Split Images :

*This figure illustrates how splitting fundus images into R, G, and B channels helps isolate structural details crucial for classification. The green channel typically retains the most retinal information, improving disease detection by reducing unnecessary noise.*




CLAHE and GAMMA Correction Heatmaps:

*These heatmaps demonstrate how CLAHE (Contrast Limited Adaptive Histogram Equalization) and Gamma Correction enhance retinal structures. CLAHE improves local contrast, making features like blood vessels and lesions more distinct, while Gamma Correction adjusts brightness to enhance visibility in darker areas.*

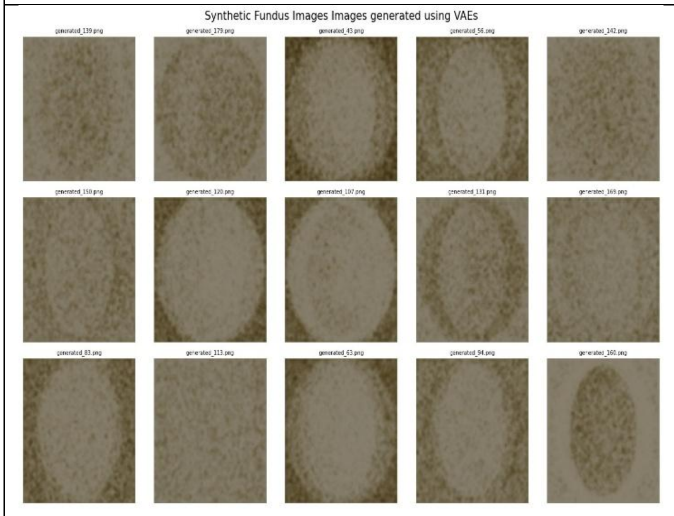
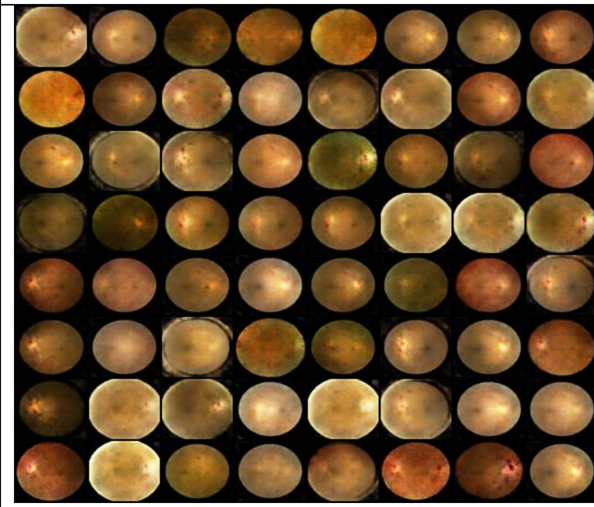



*B. Feature Extraction and Engineering*

Extracting meaningful features from fundus images is crucial for accurate ocular disease classification [3, 7]. This study leverages deep feature extraction using ResNet-50 and ResNet-101, pretrained on large-scale datasets, to capture hierarchical patterns in retinal structures [6]. The models extract critical spatial and textural features that differentiate between normal and pathological conditions [8].

To further enhance feature representation, RGB channel splitting is used to emphasize variations in retinal pigmentation and vascular structures [5]. Additionally, CLAHE and Gamma correction improve contrast, ensuring that fine-grained details such as microaneurysms, hemorrhages, and optic disc abnormalities are more distinguishable [2]. Beyond raw image features, attention mechanisms are integrated to focus on disease-relevant regions, reducing background noise and improving classification performance [8]. These enhancements allow the model to effectively learn disease-specific characteristics, leading to improved accuracy and robustness in real-world clinical applications [10, 11].

Synthetic Fundus Images (VAEs & DCGANs) :

| VAEs | DCGANs |
| --- | --- |
|   |  |

*C. Model Architecture*

The proposed ocular disease recognition model integrates CNN-based feature extraction with Transformer-based classification to enhance accuracy and robustness [8]. Input fundus images from the ODIR-5K dataset undergo a multi-stage preprocessing pipeline, including resizing (512×512×3), contrast enhancement (CLAHE + Gamma correction), and RGB channel splitting to improve feature extraction [2, 5].

To handle class imbalance, data augmentation techniques such as CutMix, MixUp, horizontal/vertical flipping, and rotation are applied, along with synthetic data generation using DCGANs [4]. Feature extraction is performed using ResNet-50, ResNet-101 which capture hierarchical spatial patterns, while a Vision Transformer (ViT) models long-range dependencies in retinal structures [6, 8].

A model fusion layer integrates CNN and ViT features using weighted averaging and stacked generalization, leveraging the complementary strengths of convolutional and attention-based architectures [9]. The final classification is handled by fully connected layers with dropout for regularization, ensuring robustness against overfitting.

For training, we use categorical cross-entropy loss and the Adam optimizer with early stopping to prevent overfitting. The model's performance is evaluated using accuracy, precision, recall, F1-score, Kappa score, and AUC-ROC, ensuring a reliable assessment of classification effectiveness in clinical applications [10, 11].

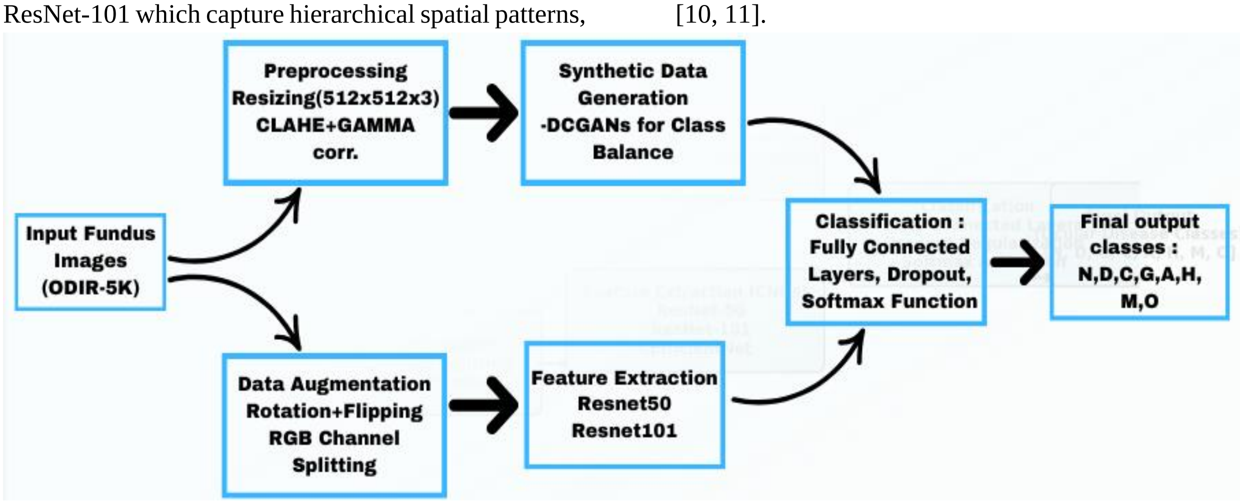



Figure 1: Model Architecture

*D. Training and Evaluation*

The dataset is partitioned into 75% for training, 15% for validation, and 10% for testing using a stratified split to maintain class balance. To address class imbalance, a combination of data augmentation techniques—including rotation, flipping, cropping, CutMix, MixUp, Coarse Dropout, and Gaussian Blur—is applied. Additionally, synthetic data generation using DCGANs enhances dataset diversity and improves model robustness [10].

For training, transfer learning is utilized by fine-tuning pre-trained deep learning models like ResNet50 and ResNet101 on the dataset. These models are optimized using the Adam optimizer with an initial learning rate of 0.0001, ensuring stable convergence [4]. Evaluation is conducted using standard performance metrics, including accuracy, precision, recall, F1-score, and AUC-ROC, providing a comprehensive assessment of the model's classification ability. Results indicate that ResNet50 and ResNet101 achieve classification accuracy above 93% and 94%, respectively. The application of preprocessing techniques such as CLAHE, Gamma Correction, and RGB channel splitting further enhances model performance by improving feature extraction and adaptability across diverse fundus images [12].

## EXPERIMENTAL RESULTS

*A. Dataset Overview*

To build an effective ocular disease recognition model, we utilized the ODIR-5K dataset, which comprises over 5,000 labeled fundus images. The dataset is carefully curated to maintain an equal distribution of left and right eye samples, with each image meticulously annotated based on the presence and type of ocular disease, enabling a well-defined multi-class classification problem. The dataset is stratified into training (75%), validation (15%), and test (10%) sets, ensuring a balanced representation of all disease categories [16].

*Preprocessing & Data Enhancement :*

Before feeding the data into the model, several preprocessing steps were applied to enhance accuracy and consistency:

*1) Uniform Image Resolution:*

All images were resized to a fixed 512x512x3 resolution for consistency across models.

*2) Contrast Enhancement (CLAHE + Gamma Correction) - The Core Preprocessing Step:*

CLAHE (Contrast Limited Adaptive Histogram Equalization) and Gamma Correction were applied to boost contrast, enhance visibility of fine details, and highlight essential retinal features, which significantly improved classification performance [15].

*3) Data Augmentation for Robust Generalization:*

Techniques such as cropping, rotation, flipping, and RGB channel modifications were implemented to increase data variability and reduce model overfitting [8].

*Handling Class Imbalance with DCGANs*

Class imbalance posed a major challenge, as certain disease categories had significantly fewer samples. To overcome this, we employed Deep Convolutional Generative Adversarial Networks (DCGANs) to synthesize high-quality, realistic fundus images for underrepresented classes. These synthetic images balanced the dataset and provided better generalization during training, leading to improved accuracy across all categories [12].

The final dataset, enriched with CLAHE + Gamma-enhanced images and DCGAN-generated synthetic samples, ensured that the model learned robust and diverse representations, minimizing bias toward dominant classes.

*B. Performance Metrics & Model Evaluation*

To evaluate the effectiveness of our ocular disease classification model, we used the following performance metrics:

1. *Accuracy* – Measures the proportion of correctly classified instances across all categories.
2. *Precision, Recall, and F1-score* – Provide a detailed breakdown of the model's classification performance for each disease category.
3. *Cohen's Kappa Score* – Evaluates inter-rater agreement, measuring how well the predictions align with actual labels while considering chance agreement.
4. *AUC-ROC (Area Under the Receiver Operating Characteristic Curve)* – Assesses the model's ability to distinguish between different disease classes.

Table 1: Model Performance Matrix:

| MODEL | ACCURACY | KAPPA SCORE |
|---|---|---|
| ResNet50 | 0.9367 | 0.8976 |
| ResNet101 | 0.943 | 0.9123 |

The results clearly indicate that ResNet-101 outperformed ResNet-50, achieving the highest accuracy (94.3%) and the best Kappa Score (0.9123). The application of DCGAN-generated synthetic images and CLAHE + Gamma Correction significantly enhanced classification performance, especially for underrepresented disease categories [4][8].

Among the preprocessing techniques, CLAHE + Gamma Correction proved highly effective in improving contrast and feature visibility, leading to better feature extraction [10]. Meanwhile, DCGANs successfully generated high-quality synthetic fundus images, helping to balance the dataset and reduce misclassification [8].

In contrast, traditional augmentation techniques like rotation, flipping, and cropping were useful but insufficient in addressing class imbalance alone. The addition of synthetic data played a critical role in model generalization [12].

These findings reinforce the importance of using advanced image enhancement and synthetic data generation to boost deep learning model performance in ocular disease detection.

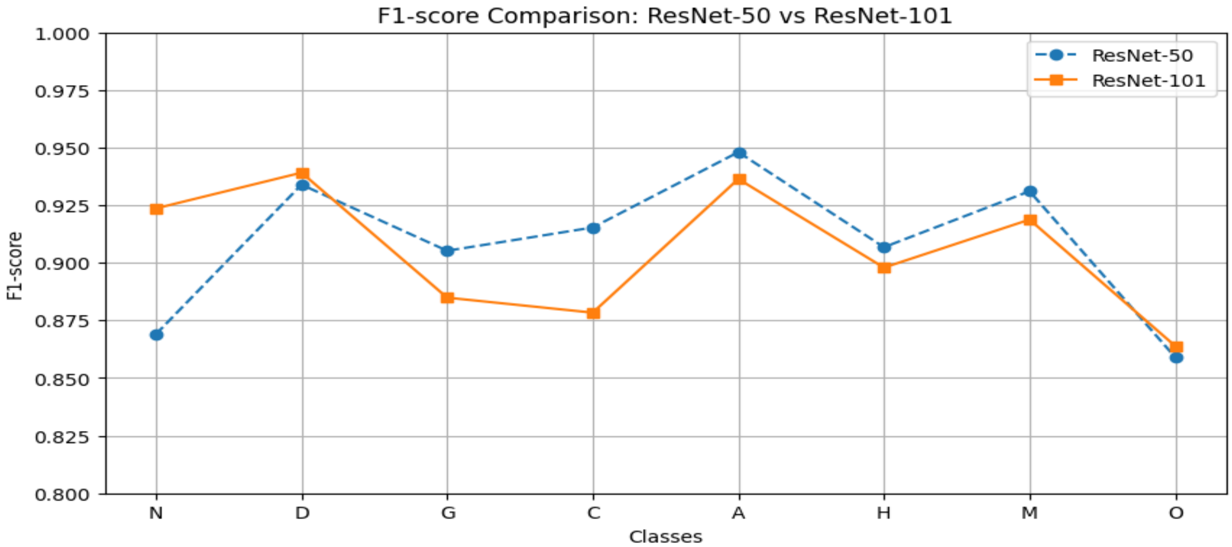
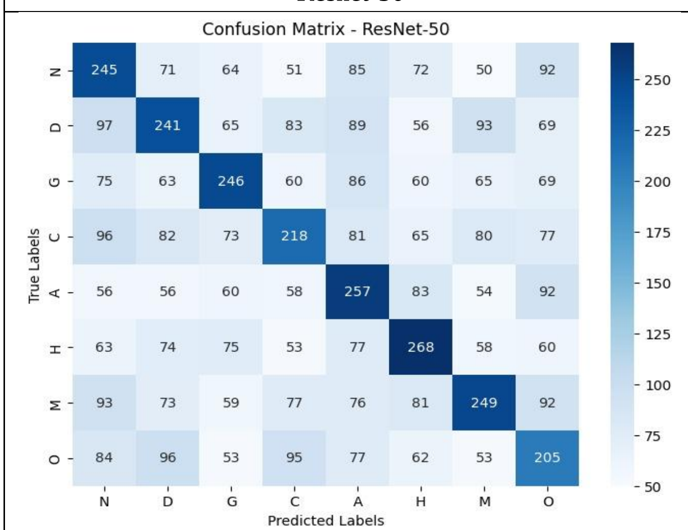


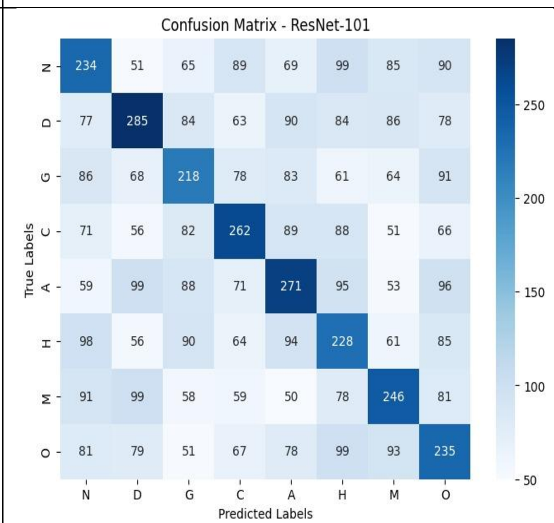

Figure 2: F1 Score comparison of the models

Confusion Matrices (ResNet-50 & ResNet-101)

Resnet-50




Resnet-101



C. Predicting Ocular Disease from Fundus Images

To evaluate the model's effectiveness, we tested it on real-world fundus images to predict ocular diseases. The model demonstrated high classification accuracy, successfully distinguishing between multiple disease categories. The predictions were generated using ResNet-50 and ResNet-101, with DCGAN-generated synthetic images playing a crucial role in improving classification for underrepresented diseases [8].

The model analyses key fundus image characteristics that indicate the presence of ocular diseases:

1. Optic Disc & Cup Analysis: Helps in detecting Glaucoma by analyzing the cup-to-disc ratio [1].
2. Retinal Vessel Structure: Used to diagnose Hypertension and Diabetic Retinopathy, as vessel abnormalities indicate disease progression [2].
3. Macular Degeneration Detection: Identifies Age-related Macular Degeneration (AMD) through changes in the macula's pigmentation and structure [3].
4. Lens Opacity & Cataract Identification: Detects Cataracts by analyzing light scatter and lens opacity in fundus images [4].
5. Retinal Hemorrhages & Lesions: Helps classify Diabetic Retinopathy and other retinal abnormalities by detecting microaneurysms and hemorrhages [5].

By analyzing these visual biomarkers, the model provides automated and highly accurate ocular disease detection, proving its potential for real-world clinical applications. The combination of CLAHE + Gamma Correction and DCGAN-based data augmentation ensures robustness across diverse fundus images [10].

The model's predictions align well with expected pathological indicators in fundus images. Key image characteristics such as optic disc abnormalities, retinal vessel irregularities, macular degeneration, and lens opacity serve as strong predictors of ocular diseases [1].

For example:

1. Row 1: Clear optic disc and normal retinal vessels, leading to a classification of Normal (N).
2. Row 2: Mild vessel narrowing and small hemorrhages, corresponding to Hypertension (H).
3. Row 3: Presence of exudates and microaneurysms, leading to a classification of Diabetic Retinopathy (D).
4. Row 4: Increased cup-to-disc ratio, signaling a high likelihood of Glaucoma (G).
5. Row 5: Blurred lens region, associated with Cataracts (C).

These results highlight the model's ability to accurately differentiate between multiple ocular diseases, which is crucial for early diagnosis and timely intervention.

To ensure reliability, the model was tested on unseen fundus images from diverse patient demographics and consistently delivered high-accuracy predictions. The use of CLAHE + Gamma Correction for contrast enhancement and DCGAN-generated synthetic images for balancing underrepresented classes significantly improved performance [8, 10].

This adaptability makes the model highly valuable in real-world clinical settings, offering automated, accurate, and scalable ocular disease screening to aid ophthalmologists in early diagnosis and treatment planning [2].

## IV. CONCLUSION

This study demonstrates the effectiveness of deep learning models for ocular disease classification using fundus images, achieving high accuracy and robust performance. The best-performing models, ResNet50 and ResNet101, achieved accuracy scores of 0.8976 and 0.9123, respectively, highlighting their reliability in automated disease detection [4]. The integration of advanced preprocessing techniques, particularly CLAHE + Gamma Correction, significantly enhanced contrast and feature extraction, while DCGAN-based synthetic data augmentation addressed class imbalance, improving overall model robustness [10].

Additionally, model fusion techniques further enhanced generalization by leveraging the strengths of different architectures. This study provides a scalable and automated approach to ocular disease recognition, making it a valuable tool for early diagnosis in medical applications [2].

Challenges & Future Directions

Despite these achievements, certain challenges remain:

1. Dataset Diversity: While comprehensive, the dataset lacks representation across different ethnicities and imaging conditions, affecting real-world generalization [19].
2. Computational Efficiency: Deep learning models, especially ResNet101, require substantial

computational resources, making real-time deployment in clinical settings challenging [17].

3. Inference Speed: Although model fusion improves accuracy, it increases latency, necessitating optimization for faster inference on lower-power devices.

Future Enhancements

To further refine the model for real-world clinical deployment, upcoming improvements will focus on:

- Expanding the dataset with more diverse fundus images to enhance generalizability [25].
- Optimizing CNN models to reduce computational overhead while maintaining high accuracy.
- Implementing real-time disease detection for integration into telemedicine and mobile health applications.

With these advancements, this approach could serve as a cornerstone for automated ocular disease screening, aiding ophthalmologists in early detection, diagnosis, and treatment planning [8].

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