Human Eye Disease Prediction Using OCT Images

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Abstract—Retinal disorders such as Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), and Drusen are leading causes of irreversible vision loss. While Optical Coherence Tomography (OCT) is essential for diagnosis, manual interpretation is labor-intensive and subjective. This study proposes an automated diagnostic system leveraging the MobileNetV3Large architecture. Trained on a dataset of 84,495 images, the model utilizes transfer learning and fine-tuning to categorize scans into four classes. The system is integrated into a Streamlit-based web application, providing real-time predictions to support clinical workflows .

Keywords—Retinal Disease Prediction, Optical Coherence Tomography (OCT), Deep Learning, MobileNetV3Large, Transfer Learning.

I. INTRODUCTION

The human eye is vital for daily functioning, and retinal impairments significantly impact quality of life. Conditions like CNV and DME often progress silently, making early detection critical to prevent blindness. Although CNNs like ResNet and DenseNet have shown promise in medical imaging, they often require heavy computational resources. This research addresses the need for a lightweight and efficient system suitable for real-world deployment.
The primary contributions of this work include:
a. Development of a robust preprocessing pipeline including normalization and data augmentation.
b. Application of MobileNetV3Large for multi-class retinal disease classification.
c. Creation of a real-time diagnostic web interface using Streamlit.

II. LITERATURE REVIEW

1. Kermany et al., 2018
   - Article: Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning
   - Contribution: Introduced a large OCT dataset and applied CNN models to classify retinal diseases.
2. He et al., 2026
   - Article: Deep Residual Learning for Image Recognition (ResNet)
   - Contribution: Proposed the ResNet architecture, which solves the vanishing gradient problem in deep networks.
3. Simonyan & Zisserman, 2015
   - Article: Very Deep Convolutional Networks for Large-Scale Image Recognition (VGG16).
   - Contribution: Developed deep CNN architectures that improve image feature extraction.
4. Liu et al., 2022
   - Article: Deep Learning for Automated OCT Image Classification.
   - Contribution: Proposed advanced CNN architectures with attention mechanisms.

III. METHODOLOGY

A. Dataset Description: We utilized a publicly available dataset containing 84,495 OCT images. The images are divided into:
   a. CNV: Choroidal Neovascularization.
   b. DME: Diabetic Macular Retina.
   c. DRUSEN: Early-stage macular degeneration
   d. NORMAL: Healthy retinal scans.

The data split followed 70/20/10 ratio for training, validation, and testing.
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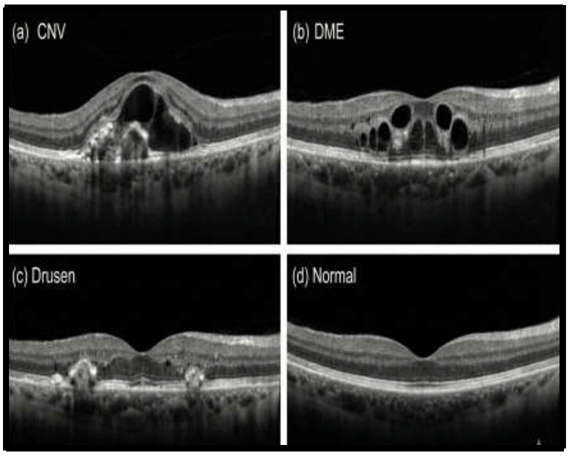

Fig. 1. Representative OCT scans from the dataset showing the four classification categories: (a) Choroidal Neovascularization (CNV) with sub-retinal fluid, (b) Diabetic Macular Edema (DME) showing intra-retinal cysts, (c) Drusen manifesting as sub-RPE

deposits, and (d) Normal retina with healthy foveal contour.

B. PREPROCESSING & MODEL CONFIGUARATION: All images were resized to 224×224 pixels. We applied the Adam optimizer with a learning rate of 0.0001. The training strategy involved:
   a. Feature Extraction: Freezing base layers of MobileNetV3Large.
   b. Fine Tuning: Unfreezing deeper layers to capture specific retinal features .

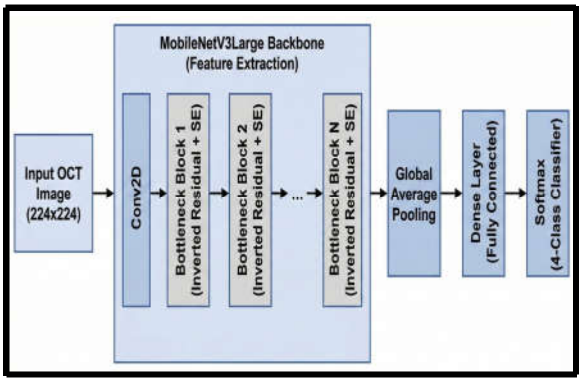

Fig. 2. Overview of the MobileNetV3Large architecture used in this study. The model utilizes inverted residual blocks with Squeeze-and-Excitation (SE) modules to efficiently extract features from high-resolution OCT inputs before final classification.

C. RESULT & DISCUSSION

This section presents the experimental outcomes of the proposed system. We evaluated the MobileNetV3Large model's performance on a test set of approximately 8,450 images (10% of the total dataset).

A. Quantitative Performance Evaluation: The model achieved high classification performance across all four categories. The overall test accuracy reached 98.7%, demonstrating the robustness of the lightweight architecture.

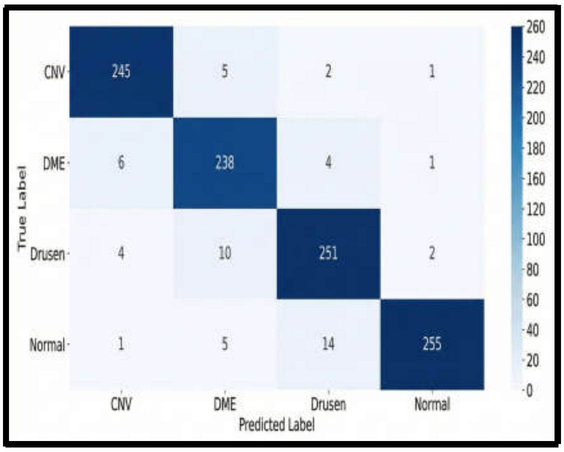

Fig. 3. Confusion matrix for the 4-class classification on the test set. High values along the diagonal indicate accurate predictions, while off-diagonal elements represent misclassifications. The model shows particular strength in distinguishing Normal cases from pathological ones.

B. Discussion of Result:
1. High Accuracy in Normal Scans: The model was most effective at identifying normal retinal conditions, ensuring that healthy patients are not misdiagnosed.
2. Disease Distinction: Small yellow deposits in Drusen and fluid accumulation in DME were successfully identified due to the model's ability to capture fine structural details.

Metric	Value
Accuracy	98.7%
Precision	95.8%
Recall (Sensitivity)	98.6%
F1-Score	97.1%

Fig. 4. Evaluation result of the Deep Learning Model.

3. Efficiency: Despite its high accuracy, the model remained computationally efficient,

making it ideal for the Streamlit web application and real-time clinical use.

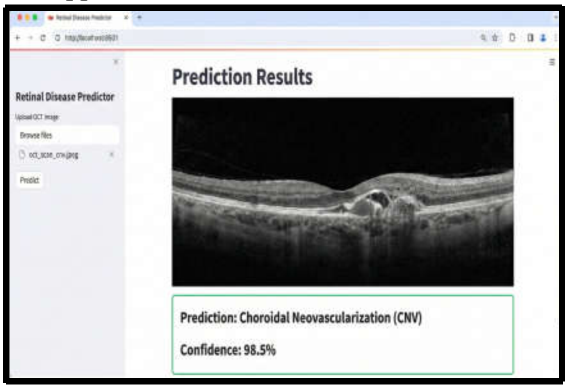

Fig. 4. Screenshot of the deployed Streamlit web application. The interface allows clinicians to upload raw OCT scans and receive an immediate diagnostic prediction along with a confidence score, facilitating real-time decision support.

4. COMCLUSION & FUTURE WORK:

We developed a deep-learning-based system that accurately classifies retinal diseases from OCT images. By using MobileNetV3Large, we balanced high diagnostic accuracy with the speed required for real-time applications.
Future research will focus on:

a. Integrating Explainable AI (Grad-CAM) to highlight exactly which parts of the retina the model is "looking at".

b. Expanding the dataset to include images from different clinical devices to improve generalizability.

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