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Classification of Human Eye Diseases Using Transfer Learning with CNN

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Abstract :Retinal conditions like Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), and Drusen are some of the leading contributors to progressive vision loss across the globe. Identifying these issues early is essential because delays in diagnosis can result in permanent retinal damage. While Optical Coherence Tomography (OCT) is commonly used by clinicians to detect such diseases, manually evaluating these images requires substantial expertise, is time-intensive, and is often influenced by observer fatigue and workload. To address these challenges, this research explores the use of MobileNetV3—a lightweight and efficient deep-learning architecture—for automatically classifying OCT images. A dataset of 109,310 images spanning four categories (CNV, DME, Drusen, and Normal) was used to train the model using transfer learning for 15 epochs. The system attained an accuracy of 95.20%, demonstrating that compact neural networks can deliver reliable diagnostic performance even in environments with limited computational power.

IndexTerms **- Optical coherence tomography, Convolutional neural network, MobileNetV3, Transfer learning, Deep learning.**

1.INTRODUCTION

Retinal disorders continue to impact millions of individuals worldwide and often progress silently until considerable vision impairment has already occurred. Diseases such as CNV, DME, and Drusen may remain undetected for long periods, especially in areas where access to ophthalmic care is limited. Therefore, timely and accurate screening is essential to prevent severe, long-term eye damage.

OCT imaging has become an indispensable diagnostic tool because it provides detailed, cross-sectional images of retinal layers, allowing clinicians to detect fluid buildup, abnormal blood vessels, and other structural irregularities. However, modern OCT machines can generate thousands of images in just one session, making manual interpretation slow and susceptible to errors caused by fatigue.

With the rapid advancement of deep learning, particularly Convolutional Neural Networks (CNNs), medical image analysis has evolved significantly. CNNs automatically learn meaningful visual features, reducing the dependence on handcrafted feature extraction. Transfer learning further enhances this by adapting pre-trained models to specialized tasks with comparatively smaller datasets.

MobileNetV3, known for its speed and compact design, is well-suited for clinical settings where high-end computing systems may not be available. This study leverages MobileNetV3 to classify OCT images into four key retinal disease classes, aiming to provide a fast, accurate, and accessible screening solution.

2.RELATED WORK

Earlier attempts to detect retinal diseases relied heavily on classical machine-learning methods, which used manually engineered features such as color, texture, and edge patterns. These features were then fed into classifiers like Support Vector Machines or Random Forests. Although these techniques laid the foundation, they struggled to interpret the complex patterns present in retinal images.

The emergence of deep learning marked a significant shift in this field. A landmark study by Kermany et al. showed that CNNs trained with large OCT datasets could achieve accuracy comparable to experienced ophthalmologists. This discovery encouraged the adoption of advanced CNN architectures such as VGG16, InceptionV3, ResNet, and AlexNet for OCT image classification, with accuracy levels typically falling between 93% and 98%. However, these models were computationally intensive, making real-time clinical deployment challenging.

More recently, researchers have turned their attention to lightweight architectures like MobileNetV2, ShuffleNet, and EfficientNet-Lite for medical applications where efficiency is crucial. Despite its improvements in both speed and performance, MobileNetV3 has not been widely explored for multiclass OCT disease classification. This study aims to address that gap by assessing the capability of MobileNetV3 while maintaining low computational requirements.

3.DATASET AND PREPROCESSING

The dataset used in this work consists of 109,310 OCT images categorized into CNV, DME, Drusen, and Normal classes. The large dataset size enhances the model's learning capacity and supports better generalization.

Before training, all images were resized to 224 × 224 pixels to meet MobileNetV3's input specifications. Pixel intensities were normalized to a 0–1 range to ensure smoother and more stable optimization.

To improve robustness and minimize overfitting, various data-augmentation techniques were applied. These included random rotations, flips, brightness shifts, and zoom adjustments. Such augmentation exposes the model to different variations of OCT images, making it more adaptable to real-world conditions.

4.METHODOLOGY

The methodology includes data preprocessing, transfer learning, fine-tuning the MobileNetV3 model, and evaluating its performance. The dataset was divided into training (76,515 images), validation (21,861 images), and testing (10,934 images) sets. Augmentation was applied uniformly to ensure balanced learning across all categories.

MobileNetV3, pre-trained on ImageNet, served as the backbone. The initial layers were retained to benefit from previously learned feature extraction patterns, while a custom classification head was added for the four disease categories. The architecture included global average pooling, dropout layers to reduce overfitting, and a softmax output layer.

Training was performed for 15 epochs using the Adam optimizer and categorical cross-entropy loss. This configuration offered a good balance between speed and accuracy.

The complete process includes five stages: image input, preprocessing, feature extraction using MobileNetV3, classification into the respective disease category, and display of the prediction. This workflow supports real-time, user-friendly screening.

5.Block Diagram

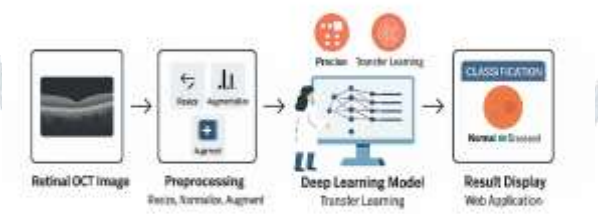

Fig. 1. Block diagram of the proposed system

The block diagram shows the complete process used in our eye disease classification system. First, an OCT image is given as input. This image goes through preprocessing steps such as resizing, normalization, and augmentation so that all images have the same size and quality. After preprocessing, the image is sent to the MobileNetV3 model, which extracts important patterns and features from the retinal scan. These features are then passed to the classification layer, which decides whether the image belongs to CNV, DME, Drusen, or Normal. Finally, the system displays the predicted disease class. This step-by-step workflow makes the model efficient, easy to understand, and suitable for real-time use in eye-disease screening.

6.RESULTS AND DISCUSSION

A. Class-Wise Performance

The model performed strongly across all categories, achieving 96% accuracy for CNV, 94% for DME, 95% for Drusen, and 96.5% for Normal. The high performance in CNV and Normal reflects their distinctive OCT features, while the slight confusion between DME and Drusen is expected due to their visual similarities.

B. Training and Validation Trends

Training and validation curves showed steady improvement, with both rising consistently over the epochs. A small gap toward the later stages suggests mild overfitting, but the overall behavior indicates good generalization.

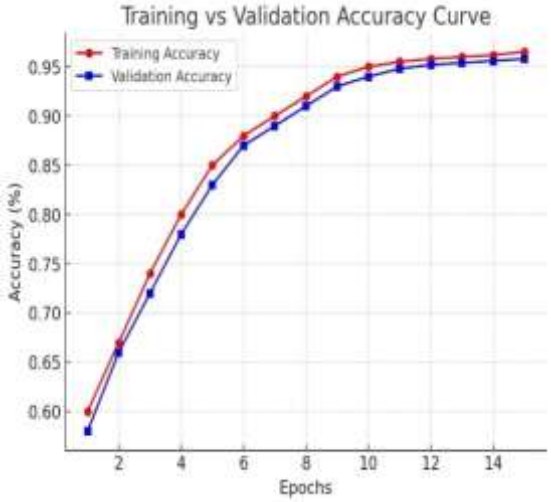

Fig. 2. Training vs. validation accuracy curve.

C. Confusion Matrix Analysis

The confusion matrix revealed that most predictions were correct, with the highest accuracy seen in CNV and Normal classes. Misclassifications were mainly between DME and Drusen, which share similar fluid-related patterns. Despite this, the number of incorrect predictions remained low, demonstrating the model's reliability.

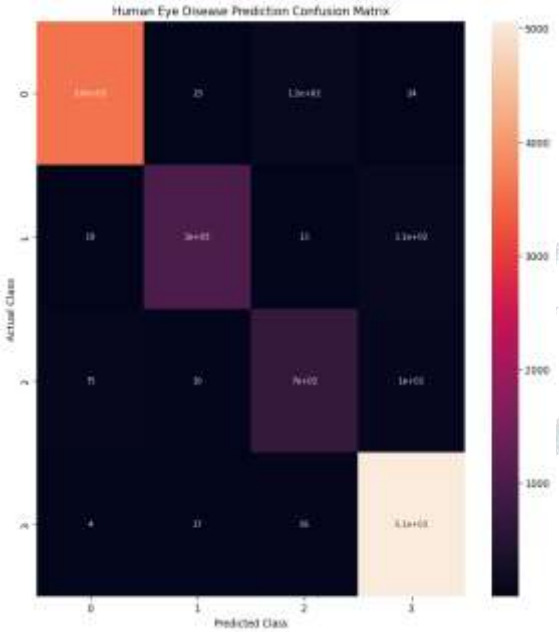

Fig. 3. Confusion matrix of classification results.

D. Overall Interpretation

The results highlight MobileNetV3's strong potential for clinical use. Its compact size, fast inference speed, and high accuracy make it suitable for screening applications, especially in areas with limited resources. Future versions of the system may include advanced techniques such as attention mechanisms or hybrid models to improve performance even further.

1. **Dashboard & Home Page**

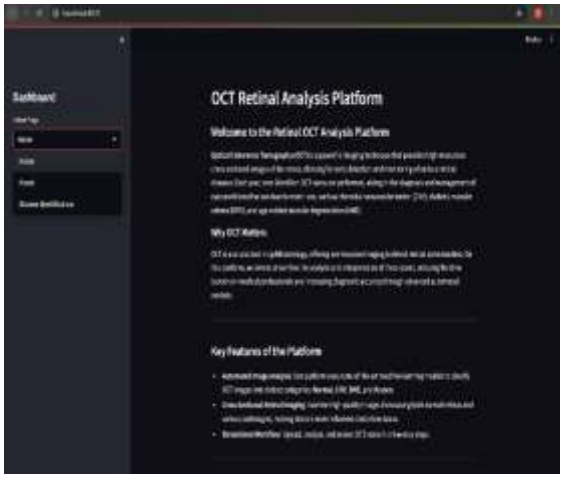

Fig .4. Home dashboard of the OCT Retinal Analysis Platform

This snapshot shows the main dashboard interface of the OCT Retinal Analysis Platform. On the left side, users can navigate between pages using a simple dropdown menu with options such as *Home*, *About*, and *Disease Identification*. The central section displays the Home Page, where the platform introduces Optical Coherence Tomography (OCT) and explains its importance in modern ophthalmology. The description highlights how OCT provides high-resolution cross-sectional retinal images, enabling early detection of conditions like CNV, DME, and Drusen. The "Key Features" section summarizes the platform's capabilities such as automated image analysis, streamlined workflow, and enhanced diagnostic support. Overall, this page helps users understand the purpose and clinical relevance of the system before proceeding to the prediction module.

2. **Disease Identification Page**

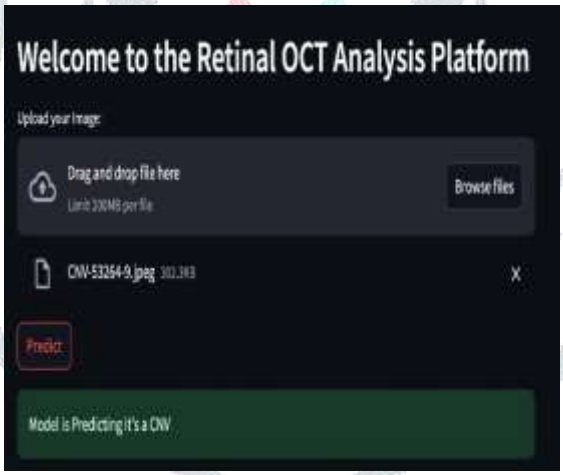

Fig .5. Model prediction showing correct classification as CNV

The prediction page is the core functionality of the platform. Users can upload an OCT image via a drag-and-drop interface or by browsing files. Once the image is uploaded, clicking the Predict button processes the scan using the MobileNetV3 deep learning model. The interface then displays the predicted class—for example, "Model is Predicting it's a CNV"—inside a highlighted output box. This page demonstrates the real-time capability of the system to classify OCT images into one of four categories: CNV, DME, Drusen, or Normal. The clean and user-friendly design ensures that healthcare professionals, students, or researchers can easily interact with the tool and obtain instant results.

3. Learn More Section – OCT Image Display

Fig .6. OCT scan showing CNV with subretinal fluid

This section is part of the *Learn More* feature, providing users with additional visual information about retinal diseases. The displayed OCT scan represents a case of Choroidal Neovascularization (CNV) with visible subretinal fluid. The goal of this section is to help users, especially non-experts, recognize how disease patterns appear in OCT images. By offering example images and descriptive text, the system enhances user understanding of retinal abnormalities and builds trust in the model's diagnostic outputs. This feature is particularly helpful for educational purposes, patient communication, and clinical decision support.

4. CNV Treatment Recommendations Page

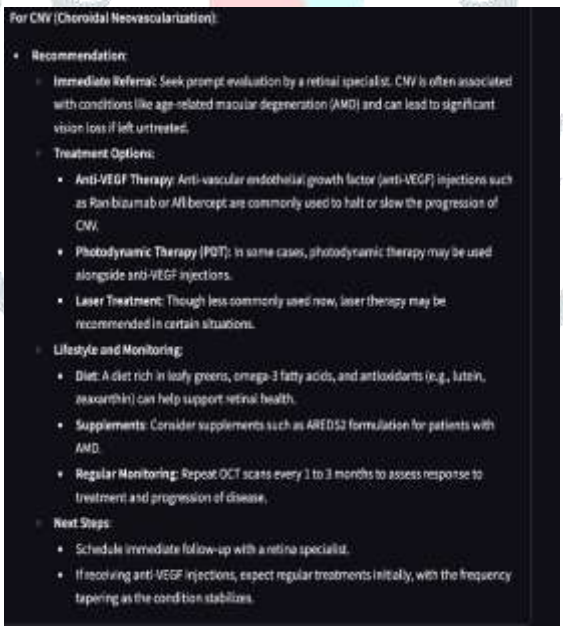

Fig .7. Disease-specific information and CNV recommendations

This snapshot displays the treatment recommendation interface that appears when the system identifies an OCT scan as CNV (Choroidal Neovascularization). The platform provides a detailed explanation of CNV and outlines appropriate clinical actions that a user may consider. The recommendations emphasize the importance of immediate referral to a retinal specialist, as CNV is often associated with serious conditions like age-related macular degeneration and can lead to significant vision loss if left untreated. The page describes common medical treatments such as anti-VEGF injections, photodynamic therapy, and, in selected cases, laser therapy. It also highlights lifestyle and monitoring practices, including adopting a diet rich in leafy greens and antioxidants, considering retinal health supplements, and undergoing regular OCT examinations to assess disease progression. Additionally, the interface guides users on immediate follow-up steps to ensure timely medical evaluation. This section enhances the platform by not only identifying the condition but also providing practical, informative guidance that supports clinical awareness and patient education.

7.CONCLUSION

This research confirms that MobileNetV3, when combined with transfer learning, is an effective approach for multi-class classification of OCT retinal images. Achieving an accuracy of 95.20%, the proposed model offers a practical and efficient

solution for early disease detection, especially in clinics lacking advanced computing systems. Although slight confusion remains between visually similar disease categories, the overall performance is consistent and promising. Future work could involve expanding the dataset, implementing explainable AI methods, and conducting real-world clinical deployments.

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