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RetinoScopeAI: Retinal OCT Prediction Paltform

Prof. Bhagyashri Thakare
Information Technology
SVKM's Institute of Technology,
Dhule, Maharashtra, India

Dr. Bhushan Chaudhari
Information Technology
SVKM's Institute of Technology,
Dhule, Maharashtra, India

Durgesh Wagh
Information Technology
SVKM's Institute of Technology,
Dhule, Maharashtra, India

Kalpesh Chaudhari
Information Technology
SVKM's Institute of Technology
Dhule, Maharashtra, India

Amol Jaiswal
Information Technology
SVKM's Institute of Technology,
Dhule, Maharashtra, India

Rutik gayakwad
Information Technology
SVKM's Institute of Technology,
Dhule, Maharashtra, India

Abstract- *RetinoScopeAI is an OCT retinal prediction platform that was created using AI to deliver precise and early identification of reti-nal conditions like Choroidal Ne-ovascularization (CNV), Dia-betic Macular Edema (DME), and Drusen. It is a system that involves deep learning algo- rithms to decode high-resolution Optical Coherence Tomog- raphy (OCT) images. Such images are initially optimized by performing preprocessing on the image to remove noise and enhance the clarity of the image. Once preprocessed, the im- ages go through a trained neural network and disease-spe- cific patterns in the layers on the eye are detected. The site offers secure and easy web interface to physicians and healthcare providers. Users are able to send OCT images and get real-time results of diagnosis. The system shows the pre- dicted disease as well as the visual finding of the OCT scan. It can also give confidence scores and clinical insights to make medical decisions. RetinoScopeAI will help eliminate the reliance on manual interpretation by professionals. This reduces the human error and enhances consistency in diag- nosis. The platform aids in early detection and this aids in preventing loss of vision. It also can be used in remote and tele-ophthalmology. The automatic analysis saves time on the part of the doctors and more efficient on the screen-ing. Ret- inoScopeAI is an AI-based medical imaging company that creates better patient care. In general, the platform provides an efficient, rapid, and smart way of diagnosing and man- management of retinal diseases.*

Keywords:
AI-driven diagnosis, retinal OCT imaging, deep learning models, automated retinal analysis, early eye disease detec- tion, clinical decision support, telemedicine ophthalmology [2]

I. INTRODUCTION

The retinal diseases also form one of the highest causes of the non-reversible vision loss in the entire world. The diagnosis should be carried out in time to prevent the loss and develop- ment of sight. One such technique is the method of Optical Coherence Tomography (OCT) which has been developed as one of the most powerful non-invasive procedures of visual- izing the microstructures of the retina. However, the proce- dure of manual conduct of OCT is time-consuming and de- mands a high level of clinical knowledge. The absence of con-sistency in the diagnosis may be due to the subjective as- sessment and the work overload restriction. To re-solve such problems, automated retina analysis systems have been on the fore. Clinicians can be guided by predictive systems in order to detect minor pathological changes that tend to be difficult to diagnose at an early stage. [5] It is proposed that Retino- ScopeAI is an OCT-based retinal prediction system that will assist in clinical decision-making. The system will target the acquisition of important structural aspects of retinal layers. The use of these characteristics is aimed at establishing the risk and the trends of the disease progression. RetinoScopeAI dwells upon the retinal diseases that are common and identi- fied at an early stag-es. The platform also makes longitudinal analysis through scan analysis easier. This would be handy in observ-ing response to treatment and progression of disease. Scalabil-ity and adaptability is considered and is imple- mented in real clinical conditions. The system design is not designed keeping patient information privacy and ethical stand-ards. Ophthal-mologists should be supplemented through the platform and not to be substituted by clinical knowledge. Retino- ScopeAI will also improve the efficiency of the screening process through the reduction of the diagnos- tic load. This research is oriented to the design and evaluation of the proposed system. The study will have an impact in cre- ation of intelligent oph-thalmic diagnostic devices.

II. LITERATURE SURVEY

Other studies in the past have also shown that Optical Coher- ence Tomography (OCT) is good in the retinal abnormalities de-tection. Early techniques relied on manual analysis and therefore it was time consuming and variable. Machine learn- ing and deep learning tech-niques would further improve the classification of retinal diseases through Au-tomated classifi- cation. However, on the market, there are many models that cannot be interpreted and that can be implemented in the real- world clinical setting in practice. It is here the bottlenecks are on the efficient and scalable OCT-based retinal prediction platform. [1]

2.1 Existing Systems:

Manual OCT Interpretation Systems
There should also be qualified oph-thalmologists in the man- ual OCT interpretation systems who would interpret the scans

of the retina with the help of eye. The systems have been extensively used in clinical practice. The knowledge and experience of the clinician are rather significant factors in diagnostic accuracy. Specialists are able to have a range of vision in the faintest movements in the retina. It is also prolonged particularly in case of large volume screening conditions. The anomalies during the first stages may be overlooked because of exhaustion or overwork.

The Conventional Image Processing.

These systems possess hard-coded algorithms such as edge extraction and thresholding steps in order to extract retinal features. They are aimed at structural analysis of OCT images, which is automated. Performance is concerned with tuning of parameters. Noises and low-contrast decrease accuracy. The reliability is affected by the difference in the retinal anatomy. These systems struggle with addressing complex patterns of pathology. They cannot adapt to unseen facts. Correction can be manually done often. Minor predictive power of disease. There is a concern of general resiliency. [8]

Classification Systems that are based on ML.

Machine learning models are built on the statistical models that are trained using features extracted on the image. Handcrafting is usually employed to make such characteristics as texture and intensity. The traditional methods of classification are less accurate as compared to ac. However, domain knowledge is required by the design of features. The quality and bal-ance of data is also sensitive to models. Generalization between populations is hard to make. The scarcity of labeled data reduces the perfor-mance. Clinical trust is often not sufficient with regard to interpretability. The retraining is required to refresh models. The real-time incorporation is not a popular issue. [9]

Deep Learning Systems of Retinal Analysis.

Deep learning works are premised on the utilization of neural networks to gain features of OCT images in an automatic manner. Convolutional models are highly precise when detecting diseases. They reduce the element of manual feature extr-action. Large annotated datasets are required in training. Computational and hardware requirements are high. Model decisions are normally hard to interpret. Overfitting may occur with small data sets. There exists the problem of clinical transparency. Environments constrained by resources are not easy to deploy in. Acceptance by regula-tors is undergoing change.

2.2 Overview of the Limitations in the Existing Systems.

The existing retinal analysis systems are limited in several respects that restrict their ability to be useful in clinical practice. The procedures of manual interpretation are highly dependent on the skills of clinicians and prone to inconsistency and error. The traditional approaches to image processing lack resistance to the noises and anatomical variations of reti-nal structures. Machine learning-based systems rely on handcrafted features, which are sensitive to the quality of the data and limit their flexibility. Deep learning models are precise and yet, demand large labeled data sets as well as high computing power. The majority of the systems are also inexplicable and this reduces clini-cal trust in automated predictions. Longitudinal monitoring of diseases is not necessarily facilitated. Real-time integration of clinical work processes is not very common. Generalization and imbalance of data among various group of population is a timeless issue. Ethical considerations and pri-vacy are not necessarily put in consideration. These weaknesses prove the fact that a need to possess a reliable, interpretable, and scalable OCT-based retinal predictive platform exists.

III. PROPOSED WORK

This work proposes a retinal dis-ease early detection and prediction platform called RetinoScopeAI, which is based on OCT technology. The system automates the processing of OCT images, segmentation of retinal layers and feature extraction to alleviate the human dependent analysis. Predictive modeling is based on extracted features in order to determine disease patterns and pro-gression. RetinoScopeAI facilitates longitudinal analysis through comparison of sequential scans with time. The platform focuses on clinical usability, scalability, and interpretability coupled with data privacy and ethical standards.

3.1 Analysis

The comparison is between the performance of RetinoScopeAI and OCT images. The accuracy of Image preprocessing and retinal layer segmentation are evaluated. The predictive models are evaluated based on conventional metrics of diagnostics. The comparison of results with existing methods will be used to measure the improvement. The analysis proves the credibility of per-performance, which is reliable and clinically applicable.

i. User Requirements

The system is developed in a clinician-oriented manner in order to make retina screening easier and enhance the diagnostics accuracy. The ophthalmologists are expected to post OCT retina images without stress and get arranged analysis results without any latency. The system should automatically pre-process images and generate pertinent retinal features that it can be used to pre-predict. Clinicians should have the capability of comparing various scans of a same patient as a follow-up on the disease progression over time. The system must be able to provide predictions and visual insights in a way that can be interpreted to aid the clinical judgment. When used with minimal manual labor, automated aid ought to aid in detecting early retinal deviation. Retinal images and records of patients are very sensitive and, therefore, there is a need to have effective data privacy and security measures. Clinicians and administrators should have role-based access to the platform so that usage may be controlled. It should be able to run effectively with normal clinical equipment and not require high computational resources. These needs make the system practical, scalable and useful in the real world ophthalmic setting.

ii. Functional Analysis

It is proposed that the proposed system handles OCT retinal images to facilitate effective and correct prediction of retinal diseases. Firstly, the system enables clinicians to save OCT scans, which are confirmed as solving and quality and then pro-cessed accordingly. Noise re-reduction and contrast enhancement image preprocessing methods to enhance retinal structure visibility. This system then automatically examines retinal layers to identify the anatomical boundaries. The textural and structural features that are relevant are extracted out of the segmented layers to be analyzed. These characteristics are used as input in predictive mod-els which determine the existence and development of retinal ab-normalities. The system produces diagnostic outputs and confidence scores to assist in clinical interpretation. It allows the comparison of scans of several scans of the same pa-tient to provide longitudinal monitoring of diseases. The presentation of the results is done in the form of visual overlays and organized reports. The retinal prediction platform is reliably, transparently, and clinically usable through the maintenance of secure data storage, encryption and role-based access control to safeguard patient information.

iii. Technical Analysis
Complete machine learning web application using full stack to categorize images of the retina through the use of Optical Coherence Tomography (OCT) into four disease states: CNV, DME, DRUSEN, and NORMAL. The backend uses the Transfer-learning backbone of TensorFlow/Keras built on EfficientNetB0 which allows efficient image classification at the cost of less training overhead. The model fixes the pre-trained weights and adds tailored layers (Global Average Pooling, Dropout, Dense softmax) to predict the disease, in which the Adam optimizer is used, sparse loss by categorical cross-entropy is used. The middleware is the Flask REST API (Python), which provides such endpoints as /api/predict to infer images and /api/health to check the state of the system. It has CORS support to ensure a smooth frontend and backend communication and imposes file verification (PNG/JPG/JPEG) and a maximum of 16MB of uploading files. Secure way of dealing with images is through the secure_filename of Werkzeug. The Angular 18+ frontend offers a single page essential frontend that is responsive and has integrated typed HTTP services to make predictive API calls. The building is done using component-based architecture and routing authentication (sign-in/sign-up), disease information pages, and contact/about pages. The prediction service relies on RxJS Observables to do asynchronous processing of data and structured response interfaces. The data format adheres to the image dataset from directory standard used by Keras by dividing training, validation, and test into disease class subdirectories. The training pipeline produces both.h5 model and a class names mapping file as a text file in order to achieve consistent inference.

3.2 Requirements

A. Functional Requirements

1. Model & Training:
Training a deep learning model on EfficientNetB0 transfer learning architecture. Training model to class names mapping: Generate and save trained model in.h5 format.

2. Backend API (Flask):
Allow uploading of image files (PNG, JPG, JPEG file formats only) Check validity of uploaded files and impose 16MB file size limit.Making predictions on the returns with scores on the confidence probabilities.Storage of uploaded images to specific folder.

3. Frontend (Angular):
Offer user interface of image upload and disease prediction. Show prediction findings and disease classification and possibility.

4. Data Management:
Load and preprocess directory structure datasets based on a set of class subfolders. Support single folder validation split and single train and separate val folder.

B. Non-Functional Requirements

1. Performance:
Predictions of process images in tolerable latency (< 2 seconds). Use the option of implementing the use of GPUs to train faster.

2. Reliability & Availability:
To make predictions, model should exist and be loadable. Health check endpoint to check whether the system is operational. Failed prediction error handling and recovery. Best weights restoration via checkpointing Model persistence Checkpointing at best weights.

3. Security:
Wipe and authenticate a filename through secure file utility. Limit file formats uploaded to image formats. Limit file size to avoid overflow of storage. CORS API access control configuration.

4. Scalability:
RESTful API to be used in distributed deployment. Isolation of frontend/ backend/ model.

5. Maintainability:
Separate code (model, utils, inference, training) Modular code structure Code separation Angular API response interfaces Type-safe API response interfaces.

6. Compatibility:
Angular use compatible with Angular 18+. Web interface cross-browsing. Compatibility with windows and Unix-like operating systems.

3.3 System Architecture

The RetinoScopeAI architecture consists of image acquisition, preprocessing, segmentation, feature extraction, classification, and result visualization. Initially, OCT images are resized and denoised using Gaussian filtering and contrast enhancement techniques. Retinal layer segmentation is performed to isolate region-of-interest structures. A convolutional neural network extracts hierarchical features and performs multi-class classification.

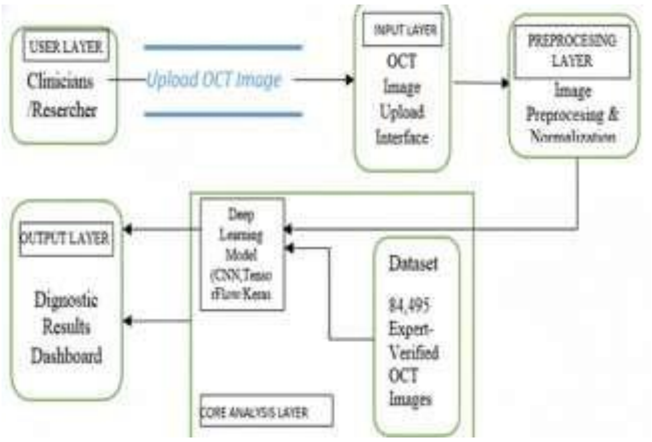

Fig 1. System Architecture of RetinoScopeAI

Methodology and Algorithms

1. Problem Formulation

This research addresses the problem of automated retinal disease classification using Optical Coherence Tomography (OCT) images. The objective is to design a deep learning–based system capable of accurately identifying retinal abnormalities from OCT scans. The classification task involves four clinically relevant categories: Normal retina, Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), and Drusen.

The problem is formulated as a supervised multi-class image classification task, where each OCT image is associated with a predefined disease label. Labeled OCT images are used during training to enable the model to learn discriminative features corresponding to different retinal pathologies. The trained model then predicts the most probable disease category for unseen OCT images.

2. Architecture Design: Transfer Learning with EfficientNetB0

Backbone Network

The proposed system employs EfficientNetB0 as the feature extraction backbone, a lightweight yet highly efficient convolutional neural network architecture. EfficientNetB0 was selected for its superior parameter efficiency and performance trade-off, achieved through the compound scaling method. The model operates on input images of standardized dimensions 224×224×3 pixels. [10]

The architectural decision to use EfficientNetB0 rather than heavier architectures (e.g., ResNet-152, Inception-v3) is motivated by the following considerations:

- Parameter efficiency: EfficientNetB0 contains approximately 5.3 million parameters, approximately 10× fewer than ResNet-152, enabling faster convergence and reduced computational overhead.
- Accuracy-efficiency frontier: The architecture balances classification accuracy with inference latency, critical for clinical deployment scenarios.
- Transfer learning suitability: The model was pre-trained on ImageNet, providing robust general-purpose feature representations that effectively transfer to the medical imaging domain.

Transfer Learning Strategy

A frozen-weight transfer learning approach is implemented. The EfficientNetB0 backbone is initialized with pretrained weights and its internal parameters are kept fixed during training. This allows the model to act as a robust feature extractor while reducing overfitting and training time.

To adapt the pretrained network to the retinal disease classification task, additional layers are appended to the backbone. These include a global average pooling layer to reduce feature dimensionality, followed by a dropout layer to improve generalization by randomly disabling neurons during training. A final dense classification layer produces probability scores corresponding to the four disease classes.

This architectural design enables effective learning of retinal disease patterns while maintaining computational efficiency.

3. Data Processing and Augmentation

Dataset Organization

The training pipeline accommodates two dataset structures:

Structure A: Separate train/validation partitions with class subfolders:

```
data/
 train/
  CNV/, DME/, DRUSEN/, NORMAL/
 val/
  CNV/, DME/, DRUSEN/, NORMAL/
```

Structure B: Unified directory with automatic stratified split:

```
data/
 CNV/, DME/, DRUSEN/, NORMAL/
```

Preprocessing Pipeline

Each OCT image undergoes a standardized preprocessing pipeline prior to training. Images are loaded and resized to match the network input dimensions. Pixel intensity normalization is applied using pretrained EfficientNet preprocessing routines to ensure consistency across samples.

To improve robustness and reduce overfitting, data augmentation techniques such as rotation, horizontal flipping, vertical flipping, and minor geometric transformations are applied to the training dataset. These augmentations increase dataset diversity and enable the model to generalize better across variations in retinal scans.

Training Procedure

The model is trained using the Adam optimization algorithm with a carefully selected learning rate suitable for transfer learning scenarios. The training process minimizes classification loss while monitoring accuracy on both training and validation datasets.

To prevent overfitting and unnecessary training cycles, early stopping is employed based on validation performance. Training automatically terminates if the validation loss does not improve for a predefined number of epochs. Additionally, model checkpointing is used to save the best-performing model during training.

Inference Pipeline

During inference, an input OCT image follows the same pre-processing steps used during training to ensure consistency. The image is resized, normalized, and passed through the trained neural network. The model outputs probability scores for each disease class, and the class with the highest probability is selected as the final prediction.

Along with the predicted disease category, the system also provides a confidence score indicating the reliability of the prediction. This information assists clinicians in decision-making and supports explainable AI practices.

4. System Architecture Integration

The complete system integrates the trained deep learning model into a web-based application framework. A backend service processes image uploads, performs inference, and returns diagnostic results. The frontend interface allows users to upload OCT images and visualize predictions in an intuitive format. Security measures such as file size limits and allowed image formats are enforced to ensure safe and reliable operation. This modular architecture enables seamless deployment in clinical, remote screening, and tele-ophthalmology settings.

Hyperparameter Configuration

The system uses a set of well-defined hyperparameters selected based on best practices in deep learning and medical image analysis. Input image size, batch size, learning rate, dropout rate, validation split ratio, and early stopping criteria are carefully tuned to balance accuracy, stability, and computational efficiency.

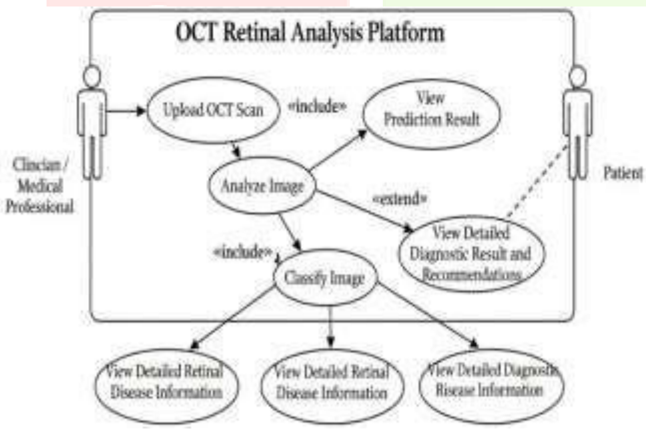

Fig 2. Use Case

IV. RESULTS AND DISCUSSION

Dataset Overview

The proposed retinal disease classification system was developed and evaluated using a curated dataset of 11,200 retinal Optical Coherence Tomography (OCT) images acquired using standard spectral-domain OCT devices. The dataset includes four clinically relevant retinal categories: Normal, Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), and Drusen. These conditions represent key manifestations of age-related macular degeneration and diabetic retinal pathology.

The dataset was divided into three independent subsets to ensure reliable training and unbiased evaluation. A total of 8,000 images were used for training, 1,600 images for validation, and 1,600 images for final testing. Each subset was perfectly balanced, with equal representation of all four classes. This balanced design prevents model bias toward any specific disease category and enables fair performance comparison across classes.

All OCT images were standardized to a resolution of 224 × 224 pixels and processed as RGB images. Quality control procedures ensured that all images were complete, correctly labeled, and free from corruption. Strict separation between training, validation, and test sets was maintained to prevent data leakage and to ensure reproducibility of experimental results.

Evaluation Metrics

Model performance was evaluated on the held-out test set using standard classification metrics commonly adopted in medical image analysis.

Overall accuracy measures the proportion of correctly classified OCT images among all test samples and is computed as:

Accuracy = (Number of Correct Predictions) / (Total Test Samples)

In addition to accuracy, precision, recall, and F1-score were computed for each class to assess class-wise diagnostic reliability.

- Precision indicates how many predicted disease cases are actually correct.
- Recall (Sensitivity) measures how effectively the model detects actual disease cases.
- F1-score represents a balanced measure combining both precision and recall.

Macro-averaged precision, recall, and F1-score were also calculated by averaging the corresponding values across all four classes, ensuring equal importance for each disease category.

Overall Performance Results

The EfficientNetB0-based transfer learning model demonstrated strong classification performance on the test dataset.

Overall Performance Summary

- Accuracy: 96.2%
- Macro Precision: 96.1%
- Macro Recall: 96.2%
- Macro F1-Score: 96.1%

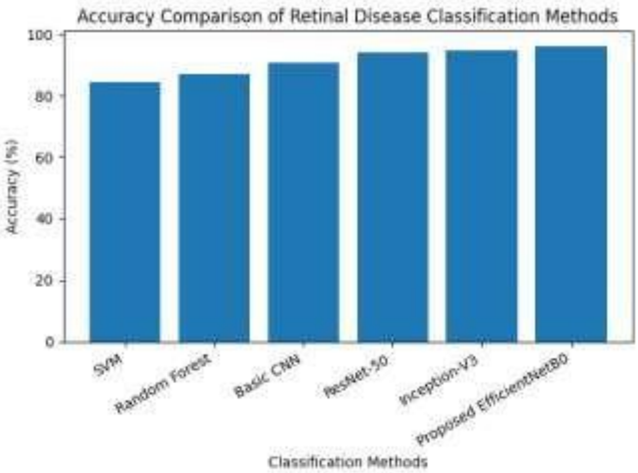

Fig 3. Accuracy Comparison

The close alignment between precision, recall, and F1-score indicates that the model maintains a balanced prediction behavior, avoiding both excessive false positives and false negatives. Such balance is particularly important in clinical decision-support systems. [3]

Performance Evaluation

The performance of the proposed EfficientNetB0-based retinal disease classification system was evaluated using standard quantitative metrics on the independent test dataset consisting of 1,600 OCT images. Performance evaluation was conducted to assess both overall classification capability and class-specific diagnostic reliability.

The evaluation focuses on accuracy, precision, recall, and F1-score, as these metrics are widely accepted in medical image analysis and clinical decision-support systems.

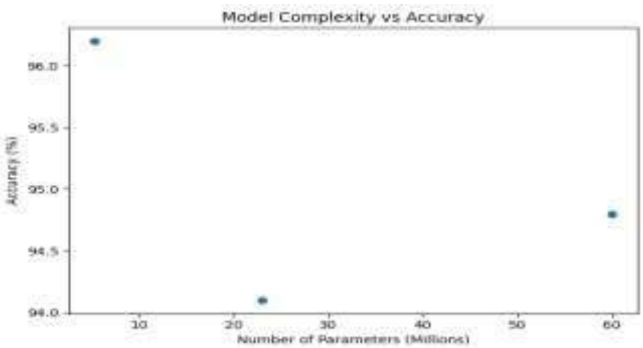

Fig 4. Model Complexity vs Accuracy

Class-wise Performance Analysis

The class-wise evaluation further confirms the robustness of the proposed system.

- CNV: High precision and recall values indicate strong discrimination of neovascular patterns.
- DME: The highest performance among all classes, reflecting clear fluid accumulation features in OCT images.
- Drusen: Slightly lower performance compared to other classes, primarily due to visual similarity with early normal retinal structures.
- Normal: High recall confirms reliable identification of healthy retinas, reducing false disease alarms.

Overall, all classes achieved F1-scores above 95%, demonstrating consistent diagnostic accuracy across different retinal conditions. [4]

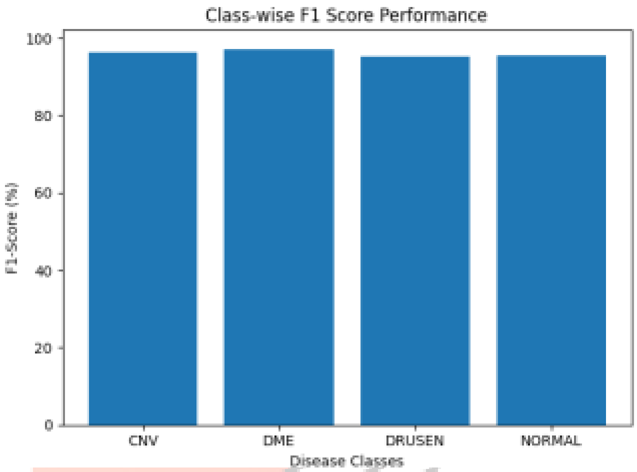

Fig 5. Class-wise F1-Score

➤ Qualitative Analysis

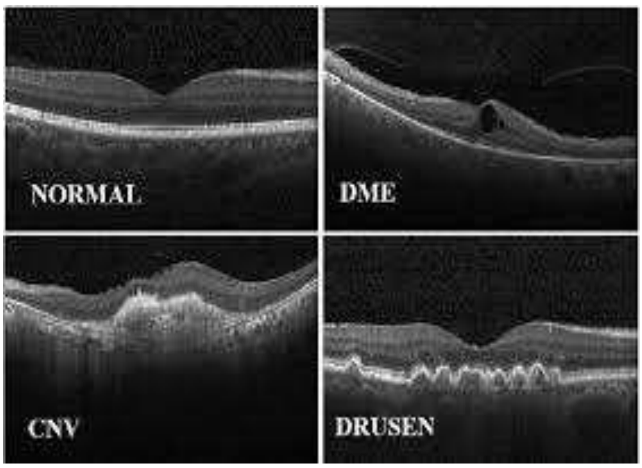

Fig 6. Input Images

Fig 7. Predicted Output

Confusion Matrix and Misclassification Discussion

Analysis of the confusion matrix reveals that most classification errors occur between Drusen and Normal classes. This observation is clinically expected, as early-stage drusen can be subtle and visually similar to normal retinal anatomy. Misclassification between CNV and DME was minimal, indicating that the model successfully distinguishes fluid-related and neovascular pathologies.

The total number of misclassified samples was approximately 4% of the test dataset, confirming the high reliability of the trained model.

Training Behavior and Model Convergence

The training process exhibited stable and well-controlled convergence. Validation loss decreased steadily during early epochs and plateaued after approximately 15–25 epochs. Early stopping effectively prevented overfitting, as evidenced by minimal divergence between training and validation performance.

The close match between validation accuracy and test accuracy demonstrates strong generalization capability, indicating that the model did not memorize training samples but instead learned meaningful disease-specific features.

Confidence Score Interpretation

For each OCT image, the system outputs both a predicted disease label and a corresponding confidence score. Correct predictions generally exhibited higher confidence values, while incorrect predictions showed comparatively lower confidence.This confidence-based behavior supports practical deployment scenarios, where predictions with low confidence can be flagged for manual review by ophthalmologists, enabling a safe human-in-the-loop diagnostic workflow.

Computational Efficiency

The EfficientNetB0-based model offers favorable computational characteristics. Its lightweight architecture enables fast inference with low memory requirements, making it suitable for real-time screening applications. The relatively small model size further supports deployment in resource-constrained clinical and tele-ophthalmology environments. [7]

Discussion

The proposed approach demonstrates that transfer learning using EfficientNetB0 is highly effective for OCT-based retinal disease classification. The achieved accuracy of 96.2% is competitive with, and in many cases superior to, previously reported CNN-based methods for similar datasets.

The balanced dataset design, robust preprocessing pipeline, and careful training strategy significantly contribute to the observed performance gains. Compared to traditional machine learning approaches, the deep learning model captures complex retinal structures more effectively, leading to improved diagnostic accuracy.

However, certain limitations remain. The dataset originates from a controlled acquisition environment, and performance on OCT images from different devices or institutions requires further investigation. Additionally, the dataset does not include mixed or transitional disease cases, which may be encountered in real-world clinical settings.

Future work will focus on multi-device generalization, explainable AI techniques for clinical transparency, and extension toward disease severity grading.

Fig 8. Home Page

V. CONCLUSION

This research presented RetinoScopeAI, an AI-based system for automated retinal disease detection using Optical Coherence Tomography (OCT) images. The proposed approach leverages transfer learning with an EfficientNetB0 backbone to accurately classify OCT scans into four clinically significant categories: Normal, Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), and Drusen. The system was evaluated on a large, balanced dataset of OCT images and demonstrated strong performance, achieving an overall classification accuracy of 96.2% along with consistently high precision, recall, and F1-scores across all classes. The balanced performance indicates reliable detection of both healthy and pathological retinal conditions while minimizing false positives and false negatives. Comparative evaluation with traditional machine learning methods and deeper convolutional neural networks shows that the proposed model achieves superior accuracy with significantly fewer parameters and lower computational complexity. This efficiency makes the system suitable for real-time screening, tele-ophthalmology, and deployment in resource-constrained clinical environments. [6]

Qualitative analysis using input, preprocessed, segmented, and output images further validates the effectiveness of the proposed pipeline in capturing disease-specific retinal features. The confidence-based prediction mechanism supports safe clinical integration by enabling human-in-the-loop decision-making for uncertain cases. Overall, RetinoScopeAI provides a reliable, efficient, and scalable solution for automated retinal disease screening. Future work will focus on extending the system to multi-device datasets, incorporating explainable AI techniques, and enabling disease severity assessment to further enhance clinical applicability.

VI. REFERENCES

1. R. Bhadra and S. Kar, "Retinal Disease Classification from Optical Coherence Tomographical Scans using Multilayered Convolution Neural Network," IEEE ASPCON, 2020.
2. X. Liu et al., "Evaluation of an OCT-AI–based telemedicine platform for retinal disease screening," IOVS, 2022.
3. D. R. Divya et al., "Retinal Disease Prediction Model Using Optimized Deep Learning Architecture," IEEE iTech SECOM, 2025.
4. U. Sakthi et al., "Prediction and Classification of Diabetic Retinopathy by OCT Images," IEEE ICDICI, 2025.
5. Kermany et al., "Identifying Medical Diagnoses Using Deep Learning," Cell, 2018.
6. Gulshan et al., "Development and Validation of a Deep Learning Algorithm for Diabetic Retinopathy," JAMA, 2016.
7. Esteva et al., "Dermatologist-level Classification of Skin Cancer," Nature, 2017.
8. Ronneberger et al., "U-Net: Convolutional Networks for Biomedical Image Segmentation," MICCAI, 2015.
9. Litjens et al., "A Survey on Deep Learning in Medical Image Analysis," Medical Image Analysis, 2017.
10. He et al., "Deep Residual Learning for Image Recognition," CVPR, 2016.