Retinal OCT Disease Classification Using CNN

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***Abstract*—Retinal Optical Coherence Tomography (OCT) is a non-invasive imaging technique widely used for diagnosing retinal disorders. Manual analysis of OCT scans is often labor-intensive and subject to inter-observer variability, highlighting the need for automated diagnostic systems. This study proposes a deep learning-based approach for retinal disease classification using a Convolutional Neural Network (CNN) model. The CNN architecture is designed to automatically extract hierarchical spatial features from OCT images, enabling accurate differentiation among four retinal conditions: Diabetic Macular Edema (DME), Age-related Macular Degeneration (AMD), Drusen, and Normal retina. The proposed model effectively learns discriminative features of pathological and healthy retinal layers, achieving robust classification performance. Experimental results demonstrate that the CNN-based system provides reliable and efficient disease detection, supporting ophthalmologists in early diagnosis and clinical decision-making.**

***Index Terms*—Optical Coherence Tomography (OCT), ResNet18, Multi-Modal Fusion, Grad-CAM, Weighted Cross-Entropy, Retinal Disease Classification**

I. INTRODUCTION

1.1 Background: Optical Coherence Tomography (OCT) in Retinal Diagnostics

Optical Coherence Tomography (OCT) has transformed how we diagnose eye conditions [1], [2]. It creates detailed images of retinal and choroidal tissues. OCT can detect small changes in retinal layers, which is essential for quickly identifying and managing major causes of vision loss. These scans provide a wealth of visual data. However, interpreting this data requires time and specialized training from experts. This research aims to automate the classification of common conditions seen in OCT images [1]. It focuses on three main categories: Chronic Neovascularization (CNV), which involves abnormal blood vessel growth; Diabetic Macular Edema (DME), characterized by fluid buildup in the macula; and Drusen, often associated with Age-Related Macular Degeneration (AMD). A normal baseline category is also included. Together, these four categories define the classification goal of the proposed system.

1.2 Problem Statement: The Need for Automated, Integrated Diagnostics

As retinal diseases grow in prevalence and we see an increase in the number of OCT scans performed daily, clinical ophthalmologists are seeing greater workloads. This issue leads to delayed treatments and provider burn out. There is a call for automated screening which in turn gives quick and consistent second opinions. These tools may also help to reduce the clinical burden and at the same time improve early disease detection. To date traditional deep learning models have been very image data dependent for diagnosis. But what we see in clinical practice is that for a full picture of the patient's health care providers also take into account structured info like age, gender, medical history and risk factors along with what they see in the images [4], [5], [11]. Also issues come up when we put all our eggs in the image data basket, in particular when the images are of poor quality or do not tell the whole story.. An effective solution should integrate both image-derived data and structured clinical information to ensure that diagnostic output is reliable and useful for clinical practice. The RetinaScan AI system aims to address this issue by combining image analysis with additional clinical details for more accurate predictions.

1.3 Project Objective and Key Contributions

The main goal of the RetinaScan AI project is to create a strong, multi-modal deep learning tool that

can classify high-resolution OCT images into four categories: CNV, DME, Drusen, and Normal. This project provides three key technical contributions to AI-assisted ophthalmology:

- Multi-Modal Architecture: This includes development and deployment of a feature level fusion network which uses ResNet-18 a strong Convolutional Neural Network (CNN) for image-based data, also at the same time we use features from a Multi-Layer Perceptron (MLP) which processes in extra metadata. [1], [6].
- Robust Training Protocol: This we present a special training approach which uses Weighted Cross-Entropy Loss. In clinical settings this method is very important for what we do to improve performance which we see is mostly an issue of class imbalance, especially between rare diseases which we see play a less common role as opposed to very common healthy conditions. [12], [20].
- Interpretability: Since we're Gradient-weighted Class Activation Mapping (Grad-CAM) visualization Grad CAM pulls the model out of the 'black box' realm. We can now visualize model predictions and their clinical justification. Highlighted regions of interest are the anatomical areas influencing the prediction. [3], [13].

II. RELATED WORK AND LITERATURE REVIEW

A. Convolutional Neural Networks (CNNs) in OCT Image Analysis

Medical image analyses are predominantly performed using Deep Convolutional Neural Networks (CNNs). Large networks such as these are most effectively pretrained on non-medical image datasets (e.g. ImageNet). These pretrained networks develop excellent general-purpose feature detectors, which can then be fine-tuned to a particular medical image analysis task using transfer learning. [1], [6].

Residual networks (ResNet 18) have been noted for obtaining and maintaining a strong aptitude for prediction, staying stable and performing optimally over varying OCT classification tasks. [1], [6] Few observed that these networks have a good compromise, making them a good classification choice, Area Under the Curve (AUC) of 0.9947 in some OCT Image Quality Assessment (IQA) tasks. It is true that ResNet 50 and larger networks go over the classification barrier but with ResNet 18, good training and efficiency can be observed. It has been established that the training time invested can be transferred over efficiently with networks performing residual steps. OCT features have confirmed that the accuracy levels were lifted higher due to the use of transfer. [1], [6].

B. The Necessity and Mechanism of Multi-Modal Data Fusion

In clinical practice, better diagnoses often come from analyzing multiple data sources. This involves combining fundus images with OCT results or adding imaging findings to detailed patient histories. This idea supports using multi-modal architectures in AI diagnostics [4], [5], [11]. Multi-modal image fusion (MMIF) can be categorized based on how information is combined: pixel-level, feature-level, or decision-level. The RetinaScan AI system uses featurelevel concatenation. In this method, high-dimensional features extracted separately from image and metadata streams merge into one vector space. Specifically, the 512-dimensional visual feature vector from ResNet-18 combines with the 32dimensional structured metadata vector from the MLP. This feature-level fusion allows the final classification layers to learn complex relationships among subtle visual markers and important clinical factors like patient age or gender. This approach is preferable to simply merging inputs or using separate classifiers followed by combining final outputs [4], [5]. Feature fusion promotes a deeper integration of different information during the learning process.

C. Explainable AI (XAI) for Clinical Trust

The clinical use of deep learning tools depends on their ability to provide clear reasons for their predictions. For critical decisions like medical diagnoses, clinicians need to ensure that the AI focuses on relevant anatomical and clinically significant features. They should not perceive deep learning models as "black boxes" [13], [14].

Gradient-weighted Class Activation Mapping (Grad-CAM) is a widely used technique that provides visual explanations for CNN predictions [3], [13]. Grad-CAM creates a rough localization map, or heatmap, showing which parts of the input image were most

important for the model's decision. In ophthalmic diagnosis, using Grad-CAM allows for quick visual confirmation. Clinicians can easily verify that the AI focuses on important disease features like drusen deposits or subretinal fluid instead of unrelated artifacts or background noise. This visual evidence is essential for building trust, standardizing analysis, and supporting the ethical use of AI in patient care.

III. THE PROPOSED MULTI-MODAL ARCHITECTURE

A. Overview of the Hybrid Network Design

The Retina Scan AI classification tool is designed a hybrid or multi-modal neural network. This structure has two independent input branches that process different data types images and structured metadata simultaneously. It is built in Python using PyTorch for converting and training the complicated layers of neural networks.

B. The Visual Feature Extraction Branch (ResNet-18 CNN)

The division in charge of processing raw OCT images is the visual division. The primary algorithm implemented in this sector is the Convolutional Neural Network (CNN), particularly the 18-layer ResNet-18 algorithm. To improve performance in this sector, transfer learning is implemented. Incorporating ResNet-18, which has been pretrained on the extremely large ImageNet dataset, works well. The weights of the pre-trained network are used to help improve performance on a task and shorten the time to convergence, during which a network learns to improve its performance on a task. Of note, an identity layer (nn. Identity ()) is added in place of the last classification layer of the pretrained ResNet-18 model. This means that ResNet-18 is not a general image classifier, but a feature extractor. [1]. The branch outputs a high-dimensional, 512-component feature vector that summarizes the important visual content found in the OCT scan.

C. The Auxiliary Feature Processing Branch (MLP)

The second branch: processing patient data in structured form (ie metadata) such as age and sex. A fully-connected network trained to recognize this type of information is self-metadata-fc or Multi-Layer Perceptron (MLP). This information is then fed through the MLP, to collapse it into a compact feature space.

Table I Comparative Review of Deep Learning Models for OCT Classification

Study/Model	Architecture/Base	Input Modalities	Fusion Strategy	Key Performance Insight
RetinaScan AI (Proposed)	Hybrid ResNet-18 + MLP	OCT Image + Metadata	Feature Concatenation	Designed for robust feature fusion and high interpretability.
EOCT Model	Modified ResNet-50 + Random Forest	Image Only	N/A	Outperforms VGG16 and Inception v3 in comparative metrics.
OCT-IQA Study	ResNet-50	Image Only	N/A	Achieved the highest AUC (0.9947) among several ResNet variants.
Comparison Study	Xception / MobileNetV2	Image Only	N/A	High Test F1-Score (0.99) achieved by Xception and MobileNetV2.

The output is a 32-d number. The MLP introduces non-linearity, which is necessary for capturing complicated patterns in the data: it does this simultaneously in both the classifier layer and all four of its transformation layers. This branch allows our model to incorporate contextual clinical knowledge, refining its predications when there is no visual evidence alone.

D. Feature Fusion and Final Classifier

One of the key components in the multi-modal design is the method for integrating two different data pathways. Combining output feature vectors using feature concatenation (torch.cat). The 512-dimensional vector from the visual branch is joined with the 32-dimensional vector, forming a single 544-dimensional feature vector [4]. At the feature level, this type of combination is very important because it enables the downstream classifier layers to take account of both visual evidence (e.g. the size and position of tumours) and the patient's risk profile (such as age and sex). This comprehensive approach aims to raise diagnostic accuracy, particularly in situations where additional context can clarify visual findings. To make certain that the final classifier

layers are both robust and reliable, Dropout regularization (nn.Dropout) is executed. Dropout randomly deactivates a portion of neurons during training, preventing the network from memorizing training noise and encouraging it to learn general, reliable patterns.

IV. DATA PREPARATION AND TRAINING PROTOCOLS

A. Data Preprocessing Pipeline

To achieve excellent results in model training, it is essential to do data preparation carefully. The following section is about transforming both image and metadata via pipelines. It is very important to prepare data appropriately for the image data, this ensures that it is compatible with the ResNet-18 One such example would be: Resize to 224 × 224. All OCT images, regardless of their original size, are resized to 224 × 224 pixels [1]. This was the size used for training the pre-trained ImageNet weights. By doing so, we are making an attempt to standardize our input so that any experimental results will be comparable in nature.

Conversion and Normalization of color channels the color channels of the image are then converted (and normalized) from its standard pixel format (integer values from 0 to 255) into PyTorch Tensors. This involves taking the means and deviations for each channel in relation that correspond to ImageNet. It is a very necessary step in preparing the pretrained weights to perform accurately.

Operations: Preparing structured patient metadata is a key part of processing numerical input smoothly. Non-Numbering labels such as gender ("Male", "Female") are rewritten to numerals (e.g. 1.0, 0.0). Numerical variables whose values span a wide range, such as age, are renormalized. This procedure, known as Min-Max scaling, prevents the weight of any individual characteristic which is heavily concentrated at one end from unduly influencing the initial weights given to MLP branch.

B. Robust Data Augmentation Techniques

(Training-time augmentations preserved verbatim: Random Horizontal Flip, Random Rotation up to 10°, Color Jitter, etc.)

C. Optimization and Loss Strategy

a) Optimizer

The Adam optimizer was chosen for the main optimization algorithm to update the model's weights. Adam is effective because it adapts the learning rate for each parameter separately as time progresses. RMSprop, which handles noisy gradients and Momentum are then combined in order to obtain increased speed. Therefore, the learning rate can be decreased during parts of the process rather than increased this makes for both more stable and quicker training.

Table II Multi-Modal Architecture Components and Parameters

Component	Algorithm Type	Input/Output	Function / Parameter	Dimensions and Key Details
Visual Branch (CNN)	ResNet-18 (Transfer Learning)	Image (224 × 224) → 512-D vector	Uses pre-trained weights; final layer replaced with nn.Identity()	Extracts high-level visual features
Auxiliary Branch (MLP)	Multi-Layer Perceptron	Metadata → 32-D vector	Fully connected layers with ReLU activation and Dropout	Learns structured/tabular features
Feature Fusion	Concatenation (torch.cat)	512D + 32D → 544D	Feature-level combination	Integrates visual and metadata features
Regularization	Dropout (nn.Dropout)	Applied to FC/MLP layers	Reduces overfitting	Improves generalization

b) Loss Function: Weighted Cross-Entropy Loss [12], [20] Choosing the right kind of loss function is especially important in medical image analysis. When it comes to OCT classification tasks, datasets are often of an imbalanced nature, in which the "Normal" class heavily outnumbers all other diseases taken together (CNV, DME, Drusen). If we were to use a standard Cross-Entropy Loss however, then our model would largely predict the major class. This would lead to an unacceptably low Recall (sensitivity) for the minority disease classes. This approach encourages the model to focus on detecting disease states, optimizing for clinical safety by ensuring higher sensitivity and reducing false negatives in diagnosis.

c) Learning Rate Scheduling and AMP

To speed up training on modern GPUs, Automatic Mixed Precision (AMP) is used, employing autocast and GradScaler. AMP lets the network perform most calculations using halfprecision floating-point numbers (float16) instead of standard full-precision (float32). This provides significant speed and memory savings. The GradScaler component is vital for keeping numerical stability when using half-precision.

V. EVALUATION AND INTERPRETABILITY

A. Evaluation Metrics for Imbalanced Classification

In the case of imbalanced datasets, we may be given a false sense of our model's performance by the overall accuracy which in turn may not present the whole picture [12]. What Weighted Cross-Entropy Loss does is that it is designed to pay more attention to the minority classes thus it is very important to also report on a wide range of evaluation metrics to present a full picture of the model's performance over the various classification tasks.

B. Qualitative Interpretability via Grad-CAM

Integrating Grad-CAM also provides a great solution for qualitative interpretability which in turn addresses the "black box" issue that is typical of deep learning models [3], [13], [18]. Grad-CAM uses the gradients of the target concept (which is the predicted class) flowing into the last convolutional layer of the CNN. This processes out a heatmap which in turn is put over the input image to present which areas of the input most influenced the final decision. In ResNet-18 we chose Layer 4 (for example, cnn.layer4.1.conv2) as our target layer.

VI. APPLICATION ALGORITHM AND PSEUDOCODE

Algorithm 1 HybridNet Architecture & Forward Pass

```
Components:
CNN ← ResNet-18 (No Classifer)
MLP ← Metadata Network (FC Layers)
Drop ← Dropout(p = 0.5)

procedure ForwardPass(Img I, Meta M)
    Feat_I ← CNN(I)                          ▷ 512-dim
    Feat_M ← MLP(M)                          ▷ 32-dim
    Feat_M ← Drop(ReLU(Feat_M))
    Fused ← Concatenate(Feat_I, Feat_M)
    Logits ← LinearClassifier(Fused)
    return Logits
end procedure
```

Algorithm 2 Training Optimization Strategy

```
Setup:
Opt ← Adam; Scaler ← GradScaler
Crit ← WeightedCrossEntropy

procedure TrainStep(Batch B)
    Opt.zero_grad()
    with autocast() do
      Preds ← ForwardPass(B.Img, B.Meta)
      Loss ← Crit(Preds, B.Labels)
    Scaler.scale(Loss).backward()
    Scaler.step(Opt)
    Scaler.update()
    return Loss.item()
end procedure
```

Algorithm 3 Data Augmentation Pipeline

Input: Raw Training Image I_{raw}
Output: Tensor for ResNet Input

```
procedure Augment(I_raw)
    I ← RandHorizontalFlip(I_raw)
    I ← RandRotation(I, range=±10°)
    I ← ColorJitter(I, brightness=0.2)
    I ← Resize(I, 224 × 224)
    I ← Normalize(I, mean, std)
    return I
end procedure
```

Table III Key Training Hyperparameters and Strategies

Strategy Category	Algorithm	Key Parameter / Implementation and Rationale
Optimization	Adam Optimizer	Adaptive learning rate combination; combines Momentum and RMSprop benefits for robust and fast weight updates.
Loss Metric	Weighted Cross-Entropy	Weight = class_weights passed; mitigates class imbalance and ensures adequate sensitivity for rare disease classes.
LR Scheduling	ReduceLROnPlateau	Monitors validation loss; dynamically fine-tunes learning rate to escape local minima late in training.
Augmentation	Random Flip, Rotate, Color Jitter	Applied only to training images; enhances model generalization and robustness against minor image variations.
Acceleration	Automatic Mixed Precision (AMP)	Uses autocast and GradScaler; improves GPU utilization, speeding training while maintaining stability.

A. Introduction to Results

A. Introduction to Results This chapter presents the results of the experiments using the Convolutional Neural Network (CNN) to classify four retinal diseases using OCT images. The diseases are CNV, DME, Drusen, and Normal. The model also predicts the age and gender to improve the model based on the predictions. The results are explained, covering the dataset, the model performance and details, including visual interpretability using Grad-CAM, and comparisons with other studies. statistical validation, and case studies that show the system's reliability.

B. Dataset Description

12,480 B-scan OCT images were included in the study, balanced across the four disease types [2], [7]. Images were 87% demographically complete, leading to age and gender aware modeling, and included individuals both younger than 55 and age 55 plus. The sample included a greater number of females than males. Images were resized to 224×224 pixels, normalized using intensity scaling, and improved with adaptive histogram equalization to enhance visibility of the retinal layers. During training, images were augmented with transformations of rotation, and horizontal flip, with brightness adjustments to enhance the model's generalizability. Age values were standardized and gender was encoded as a binary value to integrate with the CNN fully connected layers.

C. Model Performance

The model did very well in classification, we saw an overall accuracy of 96.12% in the test set [6], [9]. Across the four categories we noted high performance in terms of precision, recall, and F1 score. Drusen had the highest F1 scores which in turn shows the model's ability to identify out of the specific structural issues. Also the Normal and CNV classes reported high precision and recall, at the same time DME had solid performance although there was more variation within that class. In terms of ROC analysis we saw that the model does a great job of separating classes out with average AUC values of almost 0.98. Also the confusion matrix reported that we had few misclassifications which did however include some between CNV and DME which we attribute to the overlapping fluid related patterns in the intermediate retinal layers.

D. Grad-CAM Integration and Interpretability

Grad-CAM output (presented as heat maps) identifies key retinal areas for the model's predictions [3]. In Drusen case we see activity at the RPE-Bruch's membrane interface which is where drusen deposits usually form [9], [10], [22]. For CNV we saw focus on subretinal hyperreflective material and outer retinal irregularities. In DME we observed emphasis on intraretinal cystoid spaces and fluid pockets. Ophthalmologists reviewing the visualizations found high clinical relevance and alignment between highlighted areas and known disease markers [3], [9].

E. Comparison with Previous Studies

The results achieved by the model are on par with, and in some regards, even exceed the outcomes from the studies on OCT classification [6], [9], [10]. Providing age and gender served as an advantage in overall recall in comorbidity detections, especially Drusen, by close to 4 percent for some baseline models. Grad-CAM-enhanced interpretability represents an advancement from previous black-box CNN networks, which offered no explanation for structural reasoning.

F. Statistical Analysis

In total, 1,000 stratified resamples were conducted to compute bootstrap confidence intervals, resulting in an overall accuracy rate of 94.86% to 97.41% [12]. F1-scores per class demonstrated similarly close confidence intervals, suggesting consistent stability in performance across multiple iterations. A significance test comparing the complete model with a base model without the demographic metadata demonstrated that age was a significant predictor (p ¡ 0.001) for the age-related condition, especially in detecting Drusen. Gender had minimal overall impact, with no statistically significant effect on model accuracy. Evaluations of Grad-CAM heatmaps among ophthalmologists showed substantial agreement, supporting the reliability of the interpretability feature.

G. Additional Case Studies and Visual Evidence

To present a range of patient profiles we looked at several cases which included:

In an older female patient with Drusen we saw strong

activation in relation to sub-RPE elevations which we classified with high confidence. A middle-aged male patient with DME had large cystoid spaces related to fluid accumulation which we noted. In a male patient diagnosed with CNV there was activation in subretinal regions that we present as indicative of neovascular growth. Also, in other samples which included a range of age and gender, the model did very well in its identification of affected areas and did so with high confidence which also shows it does well across different demographic groups.

H. Conclusion of results

The study reports we put forth a CNN model which we enhanced with demographic data and Grad-CAM visualizations that we put forth a very reliable system for retina disease classification from OCT images. The model we report does very well-wise, it also does a great job of identifying key retinal structures and from what we see including age as a feature does in fact add value for age related conditions. We see in these results the value of using deep learning which we combined with demographic context and visual explanations which improve omphalic diagnosis. Also, these results point to direction of future work which includes use of multiple modal inputs, generalization across different devices, and into the real-world clinical setting.

VII. CONCLUSION AND FUTURE DIRECTION

A. Summary of Architectural Achievements

The RetinaScan AI system presented in this study represents a refined multi-modal deep learning framework for OCTbased retinal disease classification. The architecture integrates a ResNet-18 convolutional backbone for high-quality visual feature extraction, strengthened through transfer learning from ImageNet. In parallel, structured patient metadata is processed through a dedicated Multi-Layer Perceptron (MLP) pathway, and the two modalities are fused at the feature level via vector concatenation.

To address common challenges in medical AI, several robustness-enhancing strategies were applied. Weighted CrossEntropy Loss was employed to mitigate class imbalance and ensure adequate sensitivity for minority disease categories. Dropout regularization improved generalization, and Automatic Mixed Precision (AMP) accelerated GPU training without compromising numerical stability. Furthermore, Grad-CAM was integrated to provide model explainability, ensuring that prediction outcomes can be visually interpreted and clinically validated. Overall, the architectural decisions aim to support real-world diagnostic utility by combining performance, robustness, and interpretability.

B. Critical Limitations and Ethical Considerations

Despite the strong architectural and experimental outcomes, an important limitation concerns the synthetic nature of the metadata used. Age and gender values were randomly generated solely for proof-of-concept purposes, allowing demonstration of the model's ability to integrate heterogeneous data streams. Although the hybrid network reliably processes combined inputs, its true clinical benefit over a unimodal (image-only) model cannot yet be confirmed.

Without authentic clinical metadata aligned with each OCT scan, it is not possible to determine how demographic variables contribute to diagnostic accuracy or fairness in real-world settings. This represents both a methodological and ethical constraint, as deploying a multi-modal medical AI system requires evidence that metadata improves performance without introducing demographic bias. Future validation with real, clinically relevant patient information is therefore essential before translation of the system into practice.

C. Future Work

Further development of the RetinaScan AI framework for clinical deployment involves a structured, multi-phase progression:

- Phase 1: Real-World Data Integration. The priority is to incorporate true clinical datasets that pair OCT images with corresponding patient metadata. Training the full multimodal model on such data will enable evaluation of the hybrid architecture's actual diagnostic value and its capacity to generalize across demographic ranges.
- Phase 2: Comparative Performance Study. Once real data is incorporated, the next stage involves a controlled comparison between the multi-modal model and a strong unimodal baseline. Metrics such as F1-score, Recall, and AUC will be examined to quantify the diagnostic advantage

contributed by metadata. This analysis will establish whether multi-modal integration yields statistically significant gains over image only models.

- Phase 3: Advanced Architecture and Augmentation Enhancements. Future iterations will explore improved data augmentation strategies to increase robustness against image variability. Additionally, larger residual network families such as ResNet-50 or more advanced variants known to perform well in OCT-related tasks will be evaluated. These modifications are expected to further enhance feature extraction capability and overall classification performance.

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