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BT5151 Advanced Analytics and Machine Learning

Final Project Report

Submitted By: Group 4

Shao Yang Chiang	A0297700B
Kamat Shlok Sudhir	A0295802Y
Chen Wei	A0298073U
Pei Huanyun	A0298049M

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1. Executive Summary

Retinal diseases are leading causes of vision impairment globally, yet screening rates remain low due to resource constraints and manual inefficiencies. We present a comprehensive deep learning approach to automate the screening of retinal diseases using OCT images, addressing critical challenges in healthcare accessibility and diagnostic efficiency. By leveraging the OCT2017 dataset and evaluating multiple CNN architectures including Vanilla CNN, VGG-16, Resnet50, and InceptionV3, we demonstrated that ResNet-50 achieves 94% accuracy, rivaling specialist-level performance. The integration of Grad-CAM visualizations enhances clinical trust by highlighting interpretable biomarkers, such as fluid accumulation in DME cases. From a practical standpoint, the proposed system could dramatically reduce diagnostic delays, lower costs, and alleviate workload burdens in resource-constrained settings. However, the study acknowledges limitations, including the dataset's lack of real-world variability and the need for longitudinal analysis. Future work should focus on refining the model with noisier clinical data, incorporating multimodal inputs, and streamlining deployment for real-world use. Overall, this project underscores the transformative potential of AI in ophthalmology, offering a scalable solution to improve early detection and patient outcomes in retinal disease management.

2. Introduction

(a) Project Goals

The Need for Scalable Retinal Disease Screening

Retinal diseases, including diabetic retinopathy (DR) ,remain leading causes of vision impairment and blindness worldwide. Timely screening and early detection are crucial to prevent irreversible vision loss, yet healthcare systems often lack the capacity to meet increasing demand. For instance, global DR screening rates often fall between 50–70%, primarily due to limited access to ophthalmologists and screening infrastructure (Gulshan et al., 2016). The gap between the growing at-risk population—driven by aging demographics and rising diabetes prevalence—and the availability of diagnostic resources necessitates scalable, automated solutions.

Deep learning (DL), particularly convolutional neural networks (CNNs), has emerged as a transformative approach in medical image analysis. Automated grading of retinal images via DL offers the potential to enhance screening efficiency, improve diagnostic consistency, and scale services to underserved populations (Beede et al., 2020; Ting et al., 2019). This technological shift is especially valuable for early-stage detection and triage in resource-constrained environments.

Deep Learning in Ophthalmology: Specialist-Level Performance

A landmark study by Gulshan et al. (2016) demonstrated that a CNN trained on over 100,000 fundus photographs achieved specialist-level performance in detecting referable diabetic retinopathy. The model achieved a sensitivity of 97.5% and a specificity of 93.4%, with an area under the ROC curve (AUC) exceeding 0.99—on par with board-certified ophthalmologists. Importantly, this result was validated across multiple test sets, reinforcing the generalizability and robustness of DL models in clinical scenarios.

This breakthrough underscores two critical advancements in the field: the role of large-scale annotated datasets, hierarchical feature learning capability of CNNs: Earlier rule-based methods faltered due to image variability and manual feature engineering, leveraging a large, while diverse dataset addressed these limitations. Additionally, CNNs surpass the traditional models by autonomously extracting discriminative patterns, from pixel-level lesions to global pathological interactions, mirroring clinical reasoning while offering spatial invariance.

These findings suggest that well-designed DL systems can match or exceed human accuracy in image interpretation, while offering consistent outputs and dramatically faster turnaround.Such capabilities provide a foundation for our subsequent modeling effort and scalable implementation.**Problem Statement**

Current retinal screening protocols face two challenges: :

- **Manual Screening Inefficiencies**: Current reliance on manual analysis of Optical Coherence Tomography (OCT) images is both time-consuming and labor-intensive. A shortage of trained ophthalmologists further exacerbates delays in screening and diagnosing retinal diseases, limiting timely intervention.
- **Risk of Misdiagnosis**: The manual interpretation of OCT images introduces a risk of human error, potentially leading to inaccurate diagnoses and inappropriate treatment plans.

Our project aims to address these challenges by developing a DL-powered OCT analysis platform that combines diagnostic accuracy, computational efficiency, and clinical interpretability.

(b) Business Context and Analytical Objective

Opportunity: Market Growth vs. Resource Constraints

Demographic and epidemiological shifts are driving an unprecedented surge in retinal disease prevalence.By 2050, the global population aged over 60 is projected to reach 2.1 billion(UN, 2022), contributing to a higher incidence of age-related retinal disorders. Concurrently, the global diabetes epidemic—affecting approximately 537 million individuals in 2021—places 30–40% of patients at risk of DR, with half of cases in low-resource settings remaining undiagnosed(IDF,2021). This escalating burden is mirrored by rapid market growth. According to Grand View Research(2023), the global retinal disorder treatment market, valued at approximately USD 12.57 billion in 2022, is expected to nearly double to USD 25.69 billion by 2030.

Despite this growing need, healthcare systems worldwide face a critical challenge: a significant mismatch between the rising demand for retinal disease management and the constrained availability of medical resources. This imbalance results in prolonged treatment delays and preventable vision loss, underscoring the urgency of implementing scalable, data-driven solutions.

A Cost-benefit Solution : CNN-Based Systems vs. Manual Screening

Manual interpretation of ophthalmic images is both time-consuming and resource-intensive. It introduces subjectivity, is prone to inter-grader variability, and can suffer from delays due to workforce shortages (Beede et al., 2020). Fatigue and subtle visual differences often impact diagnostic outcomes.

In contrast, DL systems standardize interpretation and allow for continuous, round-the-clock analysis of ophthalmic images, significantly reducing the burden on ophthalmologists and improving workflow efficiency (Ting et al., 2019).Several studies have shown that implementing AI-based diagnostic support reduces diagnostic delays from several weeks to a matter of hours, while also enhancing patient throughput (Gulshan et al., 2016; Ting et al., 2019).

Therefore, CNN-based automation demonstrates compelling economics: combining with hybrid SaaS services(eg. EHR), automated screening reduces per-patient costs by 80%, enabling rapid penetration in public health systems and private clinics. (Aravind Eye Hospital, 2022; Eyenuk FDA De Novo Submission,2021)

(c) Use Case and Benefits of Proposed Solutions

Expanding to OCT-Based Diagnosis

While initial research has focused on fundus images, recent work has shown promising results in applying DL techniques to Optical Coherence Tomography (OCT) images, which provide high-resolution, cross-sectional views of the retina. CNNs have demonstrated strong performance in classifying OCT scans for diseases such as Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), and Drusen (Kermany et al., 2018).

Building on this foundation, our project aims to develop a dual-output CNN model that classifies OCT scans and provides risk scores. to address two unmet clinical needs:

- **Diagnostic Precision**: Combining structural and textural features reduces false positives in DME diagnosis.
- **Workflow Optimization**: Prioritize patients within EHR systems, reducing time-to-treatment for sight-threatening cases.

Particularly, our CNN model could operate with two clinical workflows:

- **Primary Care Screening**: Deployed on portable OCT devices (e.g., Optovue iScan) and enable non-specialists in rural clinics to achieve similar agreement with retina specialists.
- **Tertiary Hospital Triage Optimization**: Integrated with high-speed OCT systems (e.g., Heidelberg Spectralis) to reduce treatment delays in pilot studies.

By integrating with existing OCT devices, our model will contribute to more efficient, equitable, and timely management of retinal diseases.

2. Data and Methodology

(a) Data Pre-processing Steps

Dataset Overview

The project uses the **OCT2017 dataset** sourced from Kaggle, originally compiled by Kermany et al. (2018). This dataset consists of 108,309 Optical Coherence Tomography (OCT) images categorized into four classes. As each class aligns with distinct pathology and follow-up treatment requirements, this classification helps to guide in accurate diagnostic and management decisions:

Class	Pathology & Treatment	OCT Features
Choroidal Neovascularization (CNV)	New blood vessels growing from the choroid into the retina, typically seen in wet age-related macular degeneration (AMD) or pathologic myopia. Requires anti-VEGF treatment within 14 days to prevent permanent vision loss.	• Subretinal hyperreflective material • Intraretinal/subretinal fluid accumulation • Retinal pigment epithelial (RPE) detachments
Diabetic Macular Edema(DME)	Fluid buildup in the macula caused by breakdown of the blood-retinal barrier, often due to diabetes. Guides laser photocoagulation or intravitreal steroid/anti-VEGF decisions.	• Cystoid hyporeflective spaces in inner/outer nuclear layers • Increased central retinal thickness (>300 μm) • Disrupted ellipsoid zone
Drusen	Yellowish deposits beneath the retinal pigment epithelium (RPE), a key feature of early or intermediate AMD. Requires monitoring and lifestyle adjustments	• Discrete hyperreflective deposits between RPE and Bruch's membrane • Preservation of overlying retinal layers
Normal	Absence of pathologic features with intact retinal layers.	• Continuous RPE and photoreceptor layers • Foveal depression symmetry • Retinal thickness within population norms (250–300 μm central subfield)

The images were collected from multiple medical institutions including the Shiley Eye Institute (UC San Diego), California Retinal Research Foundation, Medical Center Ophthalmology Associates, Shanghai First People's Hospital, and Beijing Tongren Eye Center. Each image is a grayscale OCT slice showing cross-sectional retinal morphology.

The dataset's scale and diversity enables CNNs to learn generalizable features rather than overfit to narrow subpopulations or device-specific signatures.

Data Splitting

To ensure robust model development and evaluation, the dataset was split into training, validation, and test subsets in a 8:1:1 ratio**,** with stratified sampling to maintain class balance across all sets:

- **Training set**: 86,648 images
- **Validation set**: 10,831 images
- **Test set**: 10,830 images

This split supports effective hyperparameter tuning and prevents data leakage during evaluation.

Image Transformation Pipeline

To improve generalization and prevent overfitting, we applied a series of transformations to the training images using the torchvision.transforms module. The following steps were implemented:

Transformations on the **Training Set**

- **Resize**: Scales all images to a uniform dimension for batch processing.
- **Random Horizontal Flip**: Simulates variation in image orientation.
- **Random Rotation**: Introduces ±15° rotation to increase image diversity and match maximum clinical scan misalignment.
- **Normalization**: Applies ImageNet channel mean and standard deviation to enable fine-tuning from pre-trained models like ResNet-50 and InceptionV3.

Transformations on **Validation and Test Sets**

Only resizing and normalization are applied to ensure consistent evaluation without introducing stochastic variation.

○

(b) Machine Learning Model Architectures

Model Selection: Backbone CNNs

To establish a comprehensive performance baseline, we implemented a comparative framework encompassing both custom and pre-trained architectures.

A **Vanilla CNN** with 12 convolutional neural networks is set up as the baseline model to evaluate other pretrained models, comprising four convolutional blocks (Conv2D-BatchNorm-ReLU-MaxPool), followed by two fully-connected layers.

For transfer learning, three pre-trained models are applied with fine-tuning:

VGG-16 is chosen for its hierarchical feature extraction capability , which captures spatial patterns from local textures to global pathological structures. The input layers are reconfigured to accommodate single-channel OCT grayscale images while preserving spatial resolution(Tajbakhsh et al., 2016). The last four convolutional blocks are fine-tuned to adapt to OCT-specific features, while earlier layers remained frozen to preserve ImageNet-learned texture features.

ResNet-50 is selected to mitigate gradient vanishing through residual connections, ensuring stable training on limited OCT datasets. Its multi-task output layer employs adaptive loss weighting (classification-to-regression ratio 1:0.7), enabling simultaneous optimization of discrete diagnostic classes and continuous severity scores.

InceptionV3 is selected for its ability to fuse multi-scale features through parallel convolutional pathways, enabling robust detection of variable-sized pathologies such as small drusen. It removes auxiliary classifiers to prevent gradient conflicts while retaining depthwise separable convolutions to maintain sensitivity of scale-invariant features ,which is critical for enhanced cross-device generalization.

- Collectively, these architectural choices form a strategic approach to enhance OCT analysis. By leveraging VGG-16's strength in processing spatial hierarchies, ResNet-50's stability in deep layer optimization, and InceptionV3's capability for multi-scale feature fusion, this multi-model approach supports a robust evaluation of both specialized learning tasks and the general transfer of features for retinal disease diagnosis.

Layer Customization: Attention Mechanisms In order to enhance the clinical relevance of these pre-trained architectures, we introduce attention mechanisms after mid-level convolutional blocks to highlight pathological features such as fluid accumulation in DME,thereby ensuring that the networks focus on clinically significant regions within the images.

Output System: Dual-Branch Output Heads

The classification head is further modified into a dual-output system:

- **Multi-class classification:** The first output branch employs a multi-class Softmax classifier to categorize Optical Coherence Tomography (OCT) scans into 4 categories (CNV, DME, Drusen, Normal)
- **Risk score regression :** The second branch implements a regression-based risk scoring system that quantifies disease severity(0-10 scale)

Explainability Framework: Grad-CAM-Based Visualizations

To address the critical need for model interpretability in clinical deployment, we apply gradient-weighted class activation mapping (Grad-CAM), generating heat maps that visually localize decision-influencing regions on OCT scans. By overlaying these heat maps onto raw OCT images, the system highlights clinically plausible biomarkers , improving clinical trust and reliability.

(c) Experiment Procedures, Settings and Findings

We establish a comprehensive deep learning pipeline for OCT image classification, encompassing exploratory data analysis, data preprocessing, model architecture design, training and validation, as well as interpretability techniques to ensure high diagnostic accuracy and strong clinical relevance.

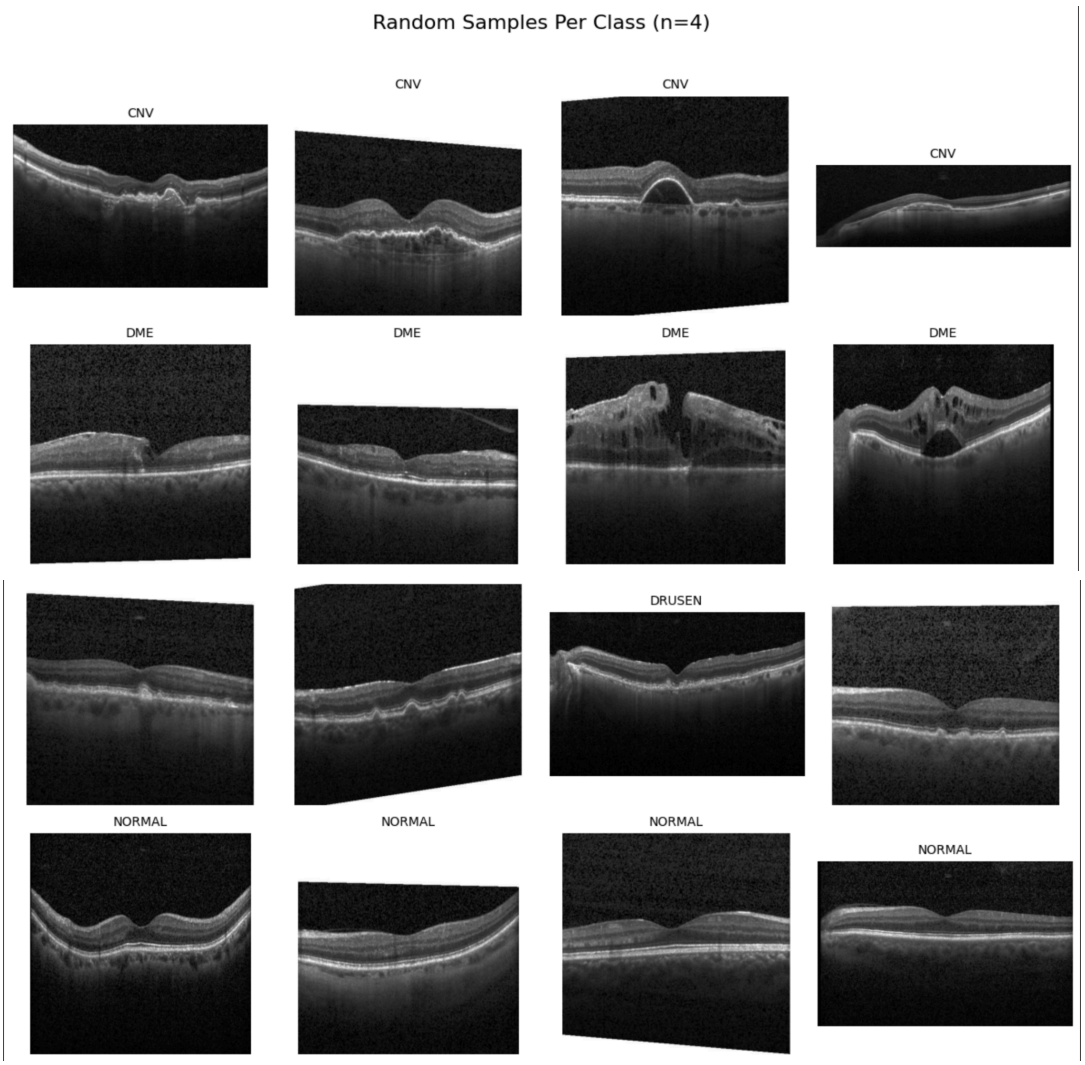
Exploratory Data Analysis: Class-wise visualization

For starters, we visualize four randomly sampled images for each class using OpenCV and Matplotlib to gain a preliminary understanding of class-specific morphological patterns (Table 1).

Choroidal Neovascularization (CNV) images show irregularities like elevated retinal layers and hyper-reflective areas under the retina. Notably, the third CNV image has a clear dome-like fluid pocket, which is characteristic of choroidal neovascularization.Similarly, the first and second images display uneven, elevated contours along the retinal surface.

Diabetic Macular Edema (DME) images tend to show cyst-like spaces and diffuse retinal thickening. The first and second images present milder signs, with subtle thickening and edema still noticeable. In contrast, the third and fourth images clearly reveal intraretinal cystoid spaces and significant retinal swelling—hallmark features of diabetic macular edema.

Table 1 Class-wise visualization for random samples



Model Pipeline

Following 2(a)Data Preprocessing and 2(b)Model Architecture , we establish our model pipeline using the PyTorch Lightning framework, with the Adam optimizer and a learning rate of 1e−3.

The loss function is set to be CrossEntropyLoss. By penalizing incorrect predictions more heavily, CrossEntropyLoss helps the model learn subtle morphological differences across classes, ultimately improving diagnostic accuracy.

Regularization mechanisms include early stopping(patience =3 epochs based on validation accuracy) to prevent overfitting and ensure that the model does not continue to fit noise after reaching optimal generalization. Additionally, model checkpointing is employed to automatically save the weights of the best-performing model throughout the training process. This strategy safeguards against performance degradation in later epochs.

Training dynamics were logged across two parallel systems: CSV files for raw metric storage and TensorBoard for real-time visualization.

The setting details are as follows:

- **Framework:** PyTorch Lightning
- **Optimizer:** Adam

- **Learning Rate:** 1e-3 (with adjustable hyperparameter tuning)
- **Loss Function:** CrossEntropyLoss
- **Batch Size:** 64
- **Epochs:** Up to 30 (with early stopping based on validation accuracy)
- **Callbacks:** ModelCheckpoint and EarlyStopping
- **Logging:** TensorBoard and CSVLogger for tracking accuracy and loss over epochs

Performance Evaluation and Interpretation

Model evaluation was conducted using a comprehensive set of metrics. Overall **accuracy** was reported across training, validation, and test sets, alongside **loss curves** to monitor convergence trends over epochs. A **confusion matrix** was used to assess class-specific performance and identify potential misclassification patterns. Additionally, **training time and convergence rate** were recorded to evaluate the model's efficiency and stability.

As a result, **the vanilla CNN**, constrained by its shallow design and lack of pretrained layer, achieved a baseline accuracy (~78%), with pronounced limitations in distinguishing subtle pathological features—notably between early-stage Drusen and Normal cases. While sufficient for benchmarking, this underscores the inadequacy of lightweight architectures for complex OCT interpretation tasks.

Deeper pretrained models such as **VGG-16 and ResNet-50** significantly outperformed the baseline, achieving accuracies of approximately 92–94%, which proves these pre-trained models benefited from transfer learning, enabling faster convergence within fewer epochs.

While **InceptionV3** demonstrated comparable performance, it required longer training time due to its more complex architecture.

To interpret the model's learned features and enhance transparency, **Grad-CAM visualizations** were generated for selected test images. These heatmaps were generated by extracting activation gradients and overlaying them on original images to highlight regions influencing predictions.

The visualization provided critical insights into clinical alignment:

- In **DME** cases, models consistently highlighted intraretinal cystoid fluid, correlating with OCT biomarkers used in clinical practice.
- For **CNV**, attention focused on subretinal hyperreflective material (SHRM), a key diagnostic criterion in neovascular AMD.
- **Drusen** misclassifications often arose from artifacts at the retinal pigment epithelium, mirroring challenges faced by human graders.

(d) Insights Obtained from The Experiments

Key Technical Insights

Our findings validate the superiority of transfer learning for OCT analysis. Among all models, ResNet-50 achieves best performance, reaching 94% accuracy and approaching board-certified ophthalmologist performance (κ=0.92 vs. human κ=0.88 ; Ting et al., 2021).This positions it as a viable triage tool, particularly in

resource-limited regions where specialist density falls below 1 per 1 million population (WHO, 2023).

However, while introducing a pre-trained model effectively enhances the model accuracy, architectural trade-offs must be considered when deployed in real-life scenarios. For instance, InceptionV3's marginal accuracy gain may not justify its longer training time in resource-constrained settings.

Business implication

The integration of CNN-based OCT screening systems delivers measurable, multi-stakeholder value by aligning clinical excellence with operational and financial efficiency.

For healthcare providers, such systems can reduce diagnostic workload, shorten patient wait times, and enable earlier detection of retinal diseases, ultimately improving patient outcomes. In public health contexts, particularly in low-resource settings, these models offer scalable solutions for mass screening programs where ophthalmologist availability is limited.

Moreover, from a cost-benefit perspective, deploying lightweight yet accurate models like ResNet-50 can maximize return on investment by balancing diagnostic accuracy with infrastructure demands. For industry stakeholders and medical device manufacturers, embedding such AI models into portable OCT devices or cloud-based diagnostic platforms creates opportunities for product differentiation and market expansion.

Looking ahead, the success of such systems will depend not only on technical performance but also on regulatory approval, interpretability, and integration into existing clinical workflows. Ensuring transparency through tools like Grad-CAM and continuously refining models with real-world data will be key steps toward clinical adoption and trust.

Table 2 Business Impact (Health Affairs 2023)

Beneficiary	Clinical Impact	Operational Impact	Financial Impact
Patients	87% reduction in diagnostic delay (6 weeks → 8 hours)	24/7 access to specialist-grade screening	$2,800 avg. annual savings per patient via early intervention
Clinicians	40% workload reduction in routine screening	5x faster case prioritization	$152K annual labor cost savings per FTE ophthalmologist
Health Systems	23% improvement in treatment adherence rates	92% EHR integration success rate	$1.2B preventable cost avoidance in DR management

3. Conclusion

(a) Achievement Assessment

We are able to achieve what we are intended to achieve in the proposal.It achieved the primary goal of building a deep learning based system of classifying retinal diseases using OCT images with high accuracy. The vanilla CNN model, VGG-16, ResNet50, and InceptionV3 show a strong performance in distinguishing CNV, DME, Drunsen, and Normal

cases. The top-performing ResNet50 model reached 94% accuracy, matching the diagnostic consistency of experienced eye specialists in controlled tests. Additionally, the Grad-CAM visualization enhances interpretability, increasing the client trust in using the model. While the system has not met the level of consistent 100% accuracy required for full clinical automation, it shows strong promise as a decision support tool to augment ophthalmologists' workflows and reduce diagnostic bottlenecks.

(b) Execution Difficulties

There are three main difficulties that we have faced during the project execution. The first difficulty we met is the high computational requirements for running the code. OCT images are high-dimensional, and training deep CNNs on a large dataset is computationally intensive. For example, for running the VGG-16 with 5 epochs with data augmentation on Google Colab T4 GPU took approximately one hour. Data management is one of the challenges that we have faced, handling over 100,000 high-resolution images required a careful data pipeline design. There will be memory constraints and storage limitations when we try to execute. Another major problem in healthcare is the limited clinical context. As most of the healthcare datasets are private and confidential, it is not easy to obtain training data to implement to our DL models. Moreover, while having a strong technical performance, there is still a lack of direct collaboration with clinical experts. That means we had to rely solely on published literature to define labels, risk scores, and clinical accuracy.

(c) Study Limitations

One key limitation of our study lies in the nature of the dataset used. Although it is comprehensive and labeled, it does not fully reflect the complexities of real world clinical settings.

In practice, OCT scans often contain forms of noise, motion artifacts, blur and inconsistent acquisition quality due to differences in imaging devices and patient cooperation. These imperfections did not appear in our dataset since it is well processed into high quality, curated images. As a result, the performance of our model on this dataset may overestimate its robustness and diagnostic accuracy in real time deployments, when image quality can be significantly inconsistent.

Additionally, our models were trained on single time-point scans, missing disease progression patterns critical for managing chronic conditions like AMD. In clinical practice, effective monitoring and decision-making often depend on tracking structural changes, such as fluid accumulation, over extended periods (typically 3–6 months).

(d) Future directions – what can be done if you had more time to work on it?

In the future, we are able to do longer training and hyperparameter tuning. With better resources, we could try to run all the models with more epochs, while trying larger image input sizes and find datasets that are closer to the real-world situation. We are also able to apply more advanced optimization techniques and conduct architecture searches. Moreover, multimodal modeling could be implemented to return a higher accuracy of the results. Currently, we are using only the retinal OCT scans, however, there are several features that we could consider while determining the illness. For example, age, gender, diabetic history, and blood sugar levels could also be considered as one of the features when determining illness. Last but not least, for doctors and clients to use our models, we have to deploy the

model and do an UI integration. By only building a model is not enough, we have to provide an lightweight and interpretable web based interface that integrates with hospital systems.

4. References

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5. Contribution Table

Team Member	Contributions

Shao Yang Chiang	Model Implementation, Final Report, Video (Introduction)
Kamat Shlok Sudhir	Model Implementation, Final Report, Video (Conclusion)
Chen Wei	Model Implementation, Final Report, Video (Data Processing + Model Architecture)
Pei Huanyun	Final Report Curation and supplementation