



Project Proposal

Advancing Ophthalmic Diagnostics with AI: A Deep
Learning Framework for Early Detection of Retinal
Diseases from OCT Data

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1. Project Overview

Ophthalmic diseases like age-related macular degeneration (AMD), choroidal neovascularization (CNV), Diabetic Macular Edema (DME), and Drusen are leading causes of blindness in the world. The diseases pose a significant public health challenge, underscoring the need for timely and accurate diagnosis of the conditions to prevent incidences of vision loss. However, despite early detection and timely diagnosis critical in preserving vision, access to ophthalmologists remains limited, especially in settings with limited resources. Manual interpretation of retinal images requires specialists, which adds to the cost of healthcare. Even where resources are available, ophthalmologists may misdiagnose patients, leading to delayed interventions. As the incidences of ophthalmic diseases increase worldwide, there is a need for scalable and efficient diagnostic systems. Advancements in artificial intelligence (AI), especially in computer vision and deep learning, have shown remarkable potential in analysing retinal images and identifying ocular abnormalities, and in some cases, exceeding human specialists. However, most of the research regarding the application of AI in retinal disease diagnosis remains largely experimental and hence not optimized for real-world deployment. This project seeks to close these gaps by proposing an AI-driven diagnostic system customized for Optical Coherence Tomography (OCT) image classification. The integration of deep learning models will enhance accuracy, efficiency, and user experience, supporting ophthalmologists in clinical workflows. This will minimize diagnostic delays, reduce costs, and ensure inclusive healthcare access. The project responds to the urgent need for technology-powered solutions that enhance ophthalmic care.

2. Project Goal

The project aims to create an AI-powered diagnostic tool that improves the detection and management of retinal conditions using automated classification of OCT images. Traditional diagnostic approaches present three main problems. Firstly, they lack the required precision to facilitate the timely detection of eye conditions, leading to delayed treatment and adversely affecting patient outcomes. Secondly, the diagnostic process using traditional methods can be time-consuming. In particular, the manual assessment of test results delays treatment, allowing eye problems to deteriorate further. Lastly, complex healthcare systems and applications inhibit patients' ability to access health information and engage in eye care. This project addresses these problems through an innovative, accurate, efficient, and user-friendly web application that facilitates the diagnosis and detection of eye conditions.

3. Approach

3.1 Data Collection

The availability of high-quality and representative data is critical for deep learning projects. This study requires a substantial amount of OCT images to facilitate the training of the system to differentiate between healthy and diseased eyes. The primary dataset will be obtained from Kaggle's Retinal OCT Images dataset. Originally compiled by Kermany et al. (2018), the dataset has been widely recognized as a benchmark for evaluating deep learning models in retinal disease classification. The dataset has 84,495 greyscale OCT images into four categories: Normal, CNV, DME, and Drusen. It is organized into three folders (train, test, val) and has subfolders for each image category. The database is well-balanced across the four categories, ensuring minimal bias

during the training and evaluation. The images were acquired under clinical conditions and are used extensively in ophthalmology studies, making them ideal for the model development in the proposed study. In addition to the Kaggle dataset, references will be made to other ophthalmic image collections like Messidor and HEI-MED. Both datasets offer fundus images with different resolutions, patient demographics, and disease stratifications. Having multiple datasets will strengthen the generalizability of the model, ensuring that it is not overfit to a single imaging protocol or population. The three datasets offer de-identified and publicly available datasets, which preserve the privacy of patients. The widespread use of the datasets in the research will ensure reproducibility and benchmarking potential.

3.2 Data Processing

Raw medical images often contain noise. While undertaking an imaging procedure, various factors introduce brightness in an image, even where no visibility detail has been captured in the image. The variation tends to be random in nature, with the presence of noise often manifesting in the form of a grainy texture, making an image appear mottled or snowy. Common types of noise in image data include quantum noise, grain and structure noise, Poisson noise, speckle noise, and electronic noise/thermal noise. Noise is problematic because it degrades image quality, obscuring critical diagnostic information. It makes it harder for clinicians to detect eye diseases and abnormalities accurately. This hinders treatment decisions due to inaccurate diagnoses, which adversely affects patients' care and treatment. As a result, preprocessing imaging data is required to clean the images and reduce noise, standardize image formats, and correct existing variations. This allows algorithms to focus on only relevant features, hence improving the reliability and accuracy of subsequent analysis. Data preprocessing will be achieved through the Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm and data augmentation.

3.2.1 Contrast Enhancement with CLAHE

CLAHE enhances the local contrast of images, especially where global contrast approaches like standard Histogram Equalization (HE) might over-enhance noise, creating unnatural appearances. CLAHE will segment the images into small tiles and redistribute the histogram values within every tile while applying a contrast clipping threshold to mitigate noise amplification (Halloum & Ez-Zahraouy, 2025). This will allow essential retinal features to remain more discernible to the model, hence supporting more reliable feature extraction by CNNs.

3.2.2 Data Augmentation

The performance of deep convolutional networks depends largely on large data sets. Improving the model's performance will require adding more image data. This will be done through data augmentation, which is a series of approaches for enlarging and enhancing the size and shape of an image, while maintaining its label (Zhang et al., 2021). The following data augmentation techniques will be systematically applied. Firstly, geometric transformations will be done through random rotations, flips, cropping, and translations to simulate variability in patient positioning and imaging angles. Secondly, color adjustments will be done by altering brightness or color intensities to simulate changes in imaging conditions. Thirdly, blurring and sharpening will be done to the imaging data to account for changes in the sharpness of the images in different devices. Lastly, random

erasing will be undertaken by removing parts of an image to allow the model to focus more on global rather than local features. Overall, data augmentation will prevent overfitting, improve accuracy, and create diversity in training data, helping the model to learn and generalize effectively.

3.3 Model/Method Selection

The core of the system will employ deep learning architectures, particularly CNNs. These are chosen because they have proved their usefulness in image classification tasks. In particular, two complementary approaches will be employed.

3.3.1 Custom-Built CNNs

A 7-layer custom CNN architecture will be used as a baseline model. This architecture consists of a network with seven distinct layers, excluding the input layer, with each part undertaking a unique operation on the data. The model will have convolutional layers containing rectified linear unit (ReLU) activations, max-pooling layers for down-sampling, and fully connected layers for undertaking the classification. While the architecture is prone to overfitting because of its simplicity, it will offer a critical insight into the behavior of the model.

3.3.2 Transfer Learning with Pre-trained Models

The availability of pre-trained large-scale models will be critical in designing the model. For instance, architectures like DenseNet121, ResNet50, and VGG16 are trained on millions of images obtained from the ImageNet dataset. As a result, these architectures offer rich feature representations that will be fine-tuned for eye disease diagnostics. Two transfer learning techniques will be explored. Firstly, feature extraction will entail freezing most of the pretrained network and training only the layers required for classification. Secondly, fine-tuning will be done to unfreeze deeper layers and retrain deeper layers on the OCT dataset to adapt learned features more closely to medical imaging.

3.4 Model Training

The dataset contains 84495 labelled OCT images, which will be split into training and testing sets, with 70% for training and 30% for testing. Further, 30% of the training data will be set aside as a validation set to check model performance during the training process. This will result in about 59,147 images for training and 25,348 for testing, with further division into 41,403 training images and 17,744 for validation. The stratification will mitigate performance metrics biases by overlapping between training and testing samples. The training model will be instrumental in running the data through the model to correlate the processed output against the sample output.

3.5 Testing and Evaluation

The trained models will be evaluated using a set of metrics: Accuracy, precision, recall (sensitivity), and specificity. And confusion matrix analysis.

5. Expected Results

The proposed system is expected to deliver significant advances in automated diagnosis of retinal diseases. It is expected to create a retinal diagnostic tool that has improved accuracy and reliability in classifying retinal diseases, including AMD, CNV, DME, and Drusen. Leveraging pretrained CNNs and applying preprocessing techniques, the project seeks to enhance sensitivity and specificity beyond traditional diagnostic approaches. Additionally, the project is expected to result in a web-based diagnostic tool that is user-friendly, multilingual (including Arabic support), and compatible with existing hospital systems. Lastly, the results are projected to have practical implications in clinical settings where the tool will minimize diagnostic delays, lower the costs associated with eye disease screening, and enhance patient engagement by empowering them with the required information.

6. Resources Needed

The successful implementation of the project will require the following resources:

6.1 Software Resources

Python will be used as the programming language because it supports machine learning and computer vision. Core libraries will include OpenCV, Scikit-image, TensorFlow and/or PyTorch, NumPy, Pandas, and Matplotlib/Seaborn. Jupyter Notebook or PyCharm will be used as the development environment for coding and experimentation. A relational database (SQLite) will be used since it is lightweight and can be embedded into the local development environment to reduce the footprint since it does not require a separate server process. This will simplify the deployment process and minimize resource usage.

6.2 Hardware Resources

The following minimal requirements will be required:

- *7th Gen Intel Core i7 processor (or equivalent).*
- *16 GB RAM for handling large image batches.*
- *256 GB SSD for storage of datasets and model checkpoints.*

6.3 Expert and Institutional Support

The success of the project will depend on collaboration with an ophthalmologist for proper data annotation, validation, and clinical relevance.

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8. Appendix

BACKGROUND AND LITERATURE REVIEW

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BACKGROUND AND LITERATURE REVIEW

2.0 Introduction

This chapter critically evaluates existing scholarship on computer-vision-based classification of OCT images for detecting Age-related macular degeneration (AMD), choroidal neovascularization (CNV), Diabetic Macular Edema (DME), Drusen, and normal retinal conditions. The chapter demonstrates OCT classification within the broader evolution of medical image analysis with attention to deep learning models that promise to enhance diagnostic accuracy and clinical scalability.

2.1 Background on Eye Conditions

2.1.1 The Human Visual System: An Overview

Humans are remarkably dependent on the visual system to get information and understand their surroundings. It is responsible for processing images and perception, allowing individuals to see shapes, colours, movement, and to identify objects. Researchers indicate that more than 70% of human information is collected by vision, making vision the most critical sensor of a normal human being (Mandal, 2003). At the heart of this system are coordinated actions or anatomically distinct structures consisting of external and internal components, all working together to convert light into neural signals. The external structure consists of the visible parts of the eye, like the sclera, conjunctiva, cornea, iris, and pupil. The sclera is the white visible portion, which is made of dense tissue and protects the inner parts. The conjunctiva is the transparent and thin layer covering the sclera. It is made up of stratified squamous epithelium and keeps the eye moist and clear. The cornea is the transparent front part of the eye covering the pupil and the iris. In addition to protecting the inside of the eye, the cornea refracts the light along with the lens. The iris is the pigmented, coloured part of the eye, visible externally. It controls the size of the pupil depending on the light source. The pupil is the black circle inside the iris. It widens and narrows to control the amount of light entering the eye. The internal structure of the eye has the following components: lens, retina, optic nerve, aqueous humour, and vitreous humour. The lens is the transparent and biconvex part of the eye. Together with the cornea, the lens refracts light so that it focuses on the retina. The retina is the innermost layer of the eye. It is the thin layer of light-sensitive cells at the back of the eye that converts light into electrical signals. The optic nerve carries all the nerve impulses from the retina to the human brain. The aqueous humour is a watery fluid between the cornea and the lens. It keeps the

eye nourished and inflated. The vitreous humour is a transparent, jelly-like substance between the lens and the retina. It protects the eye and maintains its spherical shape. The complexity of the different layers underscores why pathological changes profoundly degrade vision. Due to the biological complexity, automated diagnostic systems must accurately detect subtle morphological changes in OCT scans to avoid instances of false negatives that could cause late interventions (Du *et al.*, 2024).

2.1.2 Age-Related Macular Degeneration (AMD)

A landmark Beaver Dam Eye Study (BDES) served as a pioneering modern epidemiologic study in AMD (Chew, 2020). The BDES involved a long-term, population-based study that studied the prevalence, incidence, and risk factors associated with age-related eye disease. The research began in 1987 and focused on a population in Beaver Dam, Wisconsin, between 43 and 86 years. The study established that CNV associated with age-related AMD was at 1.2% among all older adults within 43-86 years (Chew, 2020). A recent study examined the global burden and trends in AMD-related low vision and blindness from 1999 to 2021 and projected through 2050 (Zhang *et al.*, 2024). The results demonstrated an increase in the number of prevalent cases of AMD from 3,640,180 in 1990 to 8,057,521. This number is further projected to increase to 13,880,610 by 2050 (Sheng *et al.*, 2021). A variety of environmental and genetic risk factors are associated with AMD. Aging remains the most non-modifiable environmental risk for AMD (Salimiaghdam *et al.*, 2019). Additionally, studies have shown that ethnicity and gender are significant non-modifiable risk factors, with white females at a higher risk of the late forms of AMD compared to black individuals (Rudnicka *et al.*, 2015). Other factors for the prevalence of AMD include smoking, higher body mass index, and cardiovascular disease (Mauschitz & Finger, 2022; Kráľová *et al.*, 2024).

2.1.3 Choroidal Neovascularization (CNV)

CNV entails the proliferation of fragile choroidal blood vessels beneath the retina, often associated with wet age-related macular degeneration (AMD). It can be clinically concomitant with various symptoms such as extreme myopia and malignant myopic degeneration (Sheng *et al.*, 2021). Traditional diagnoses like fluorescein angiography (FA) have been widely used for CNV (Uchida *et al.*, 2018). FA utilises a special dye and camera to visualise the flow of blood in the retina and choroid, assisting in determining the presence of leakages. However, FA is invasive, requiring intravenous dye injection, which may cause discomfort, nausea, and occasionally anaphylaxis (Chiu & Chu, 2022). Furthermore, the approach is time-consuming, requiring 15-20 minutes to complete, which may cause delays in busy clinics.

2.1.4 Diabetic Macular Edema (DME)

DME is a complication of diabetic retinopathy where fluids accumulate in the macula, causing the thickening of the retina. The swelling can cause blurry vision, impact the performance of normal daily activities, and potentially cause blindness if left unchecked. DME is a result of diabetic retinopathy, where high blood sugar causes damage to blood vessels in the retina. Symptoms include colours appearing faded, gaps in vision, and blurry vision. Since early DME does not have noticeable symptoms, people must undergo regular checkups. Risk factors for DME include poorly controlled diabetes, longer duration of diabetes, high blood pressure, kidney diseases, and high cholesterol. There are various conventional diagnostic approaches for DME. Firstly, Stereo Fundus Photography entails taking two photographs of the retina from multiple angles to get a three-dimensional image. The procedure assists in documenting the appearance of the macula and assessing the changes in the retina. Additionally, Slit-Lamp Biomicroscopy permits the clinical examination of the macula using a

stereoscopic view to establish its structure. The procedure allows the ophthalmologist to visualise retinal thickening and other signs of DME directly. Furthermore, FA and OCT are also utilised to detect DME, with OCT being the primary diagnostic tool because of its ability to offer detailed and high-resolution images of the retina to establish macular thickness.

2.1.5 Drusen

Drusen entails extracellular deposits beneath the retinal pigment epithelium and is significantly associated with early AMD. The yellowish deposits accumulate under the retina, particularly between the retinal pigment epithelium (RPE) and Bruch's membrane. Drusen is common among older adults and can be a sign of AMD, with their presence, size, and number predicting the disease progression. Few hard drusen may not significantly affect vision, but large soft drusen are associated with a higher risk of vision loss. It is important to note that while Drusen bodies are commonly described in AMD, they are not pathognomonic of AMD. VanDenLangenberg & Carson (2023) indicate that Drusen-like deposits have been observed in some less prevalent inherited conditions like Sorsby fundus dystrophy.

2.1.6 Summary: Burden and Diagnostic Challenges

Conventional diagnostic techniques for retinal conditions like AMD, CNV, DME, and Drusen have long been used in clinical practice. However, these traditional approaches have various limitations that impact diagnostic accuracy and disease monitoring. A primary concern is their subjective nature, as a majority of techniques, such as ophthalmoscopy and slit-lamp biomicroscopy, often depend primarily on the clinician's visual interpretation and analysis. Inter-observer variability due to their subjective nature reduces reproducibility. Further, the techniques are unable to quantify retinal edema or drusen volume, making it challenging to assess the progression of the disease. For instance, despite fundus photography showing drusen, it cannot indicate the subtle thickening of fluid accumulation associated with early DME, allowing the disease to become more severe without detection. Additionally, conventional approaches have poor sensitivity, allowing early-stage pathology frequency to progress undetected. The inability to offer three-dimensional imaging capabilities makes it difficult to assess layer-specific changes in the retina. While conventional approaches are widely used in the diagnosis due to their accessibility and cost-effectiveness, they are increasingly being replaced with more advanced imaging techniques like Optical Coherence Tomography (OCT).

2.2 Optical Coherence Tomography (OCT) in Ophthalmology

2.2.1 Fundamentals of OCT Imaging

The need for non-invasive medical interventions is critical to the rapid growth of the medical management of disease, especially when dealing with delicate organs (Zeppieri *et al.*, 2023). Imaging procedures eliminate the risk of trial-and-error medicine and the burden of invasive exploratory approaches before the start of treatment. In the earlier days, the visualisation of ocular structures and physical investigations were limited to techniques like ophthalmoscopy and tonometry, in addition to information obtained from the reported symptoms. The introduction of OCT offers a non-invasive imaging technique to detect CNV without the intravenous dye (Nikolopoulou *et al.*, 2018). OCT was first reported in 1991, with its clinical application dramatically improving in sensitivity and specificity over the years. The technique produces high-resolution cross-sectional images of the retina by measuring the echo delay and intensity of the backscattered light. This allows the visualisation of ocular structure and the quantification of multiple retinal and eye-related structural parameters. Hence, the approach offers both qualitative (morphology and reflectivity) and quantitative (thickness,

mapping, and volume). Unlike earlier imaging modalities like FA, OCT permits real-time visualisation without the need for contrast agents, reducing patient discomfort and associated risks. According to Oliveira *et al.* (2025), OCT's ability to delineate microstructural changes in the retina allows early detection of disease markers that may not be visible to traditional fundoscopy. Consequently, OCT has become a standard for diagnosing retinal conditions.

2.2.2 Limitations of Traditional OCT Analysis

However, researchers warn that OCT is limited since it is only sensitive to the backscattering light intensity; hence, it is unable to differentiate between vasculature from fibrous and other surrounding tissues (Leitgeb *et al.*, 2014; Subban & Raffel, 2020). The limitation makes OCT a supplement of FA and not a replacement in the diagnosis of CNV and other eye diseases. Additionally, researchers argue that OCT interpretation remains dependent on subjective visual assessment, which makes it vulnerable to variability and potential errors. Studies have demonstrated significant disagreements among observers when interpreting OCT images, mainly where subtle abnormalities occur during the early stages (Du *et al.*, 2024; Goździewska, Wichrowska & Kocięcki, 2023). This variability can lead to misdiagnosis, delayed treatment, and negative implications for patient care. Moreover, OCT is costly compared to traditional diagnostic techniques, making it less accessible to lower-income patients. The high costs come from manual analysis of OCT images, which is time-intensive. This places significant strain on ophthalmology clinics in regions with limited specialist availability. OCT equipment requires a high level of maintenance, which further limits its application in low-resource settings. Further, static OCT images can be blurred and infested with segmentation errors, especially among patients with poor fixation (Falavarjani *et al.*, 2022; Cui *et al.*, 2019). The limitations of OCT have given rise to a growing demand for automated diagnostic procedures that standardise image analysis, minimise diagnostic latency, and extend to resource-constrained environments.

2.3 Computer Vision and Deep Learning in Medical Imaging

2.3.1 Evolution of AI in Medical Image Analysis

AI refers to a wide range of technologies seeking to give machines the ability to undertake human-like cognitive functions. The first abstract models of intelligent machines emerged in the 1940s. The 1950s and 1960s saw the emergence and development of machine learning algorithms like decision trees. More recent advancements have refined learning algorithms and led to the development of convolutional neural networks (CNNs) that process and analyse images more efficiently. The renewed development has been accelerated by the increase in computing power with graphical processing units (GPUs) and the availability of large datasets (Avanzo *et al.*, 2024). The advances in AI have found their application in medicine, with the technology already widely used in various medical roles, such as imaging. According to Fazal, Patel, and Gupta (2018), the widespread use of AI in imaging is partly due to the recognition of the frequency of clinical errors in radiology reporting and the promise that the technology can improve the reliability of the process. As a result, computer vision applications in healthcare have expanded to include radiography, pathology, dermatology, and ophthalmology among other areas. Researchers argue that the ongoing technological advancements point to a future where computers may supersede the role of the radiologist and ophthalmologist, and hence eliminate human error (Fazal, Patel, & Gupta, 2018). Nonetheless, the integration of AI in diagnosis raises questions about integration into existing clinical workflows (Alowais *et al.*, 2023; Nasef *et al.*, 2025).

2.4 Dataset Landscape for OCT Image Classification

2.4.1 Publicly Available OCT Datasets

The development of accurate and generalisable deep learning models for OCT classification relies heavily on the availability of annotated datasets. The availability of large, real-world datasets is essential in accelerating research for eye disease diagnosis, since ML models need meaningful data at a sufficient scale. Such data exists, since a majority of the healthcare institutions have clinical imaging data at scale. However, Khan *et al.* (2021) warn that such imaging data tends to be inaccessible to researchers. Barriers emanate from the inability to navigate the governance frameworks that regulate data usage. Cost barriers may emerge when accessing the data requires significant resources, particularly for datasets that charge a fee. Time barriers are common, especially for datasets requiring more time before they are made available. Even where imaging datasets are available, the data may not be of good quality and accurately labelled (Khan *et al.*, 2021). To bypass these challenges, researchers turn to publicly available imaging datasets. One of the most prominent is the Kermany *et al.* dataset, hosted on Kaggle (2018), which includes over 207130 OCT B-scan images across four categories: CNV, DME, drusen, and normal. It remains one of the most widely used datasets for benchmarking deep learning models due to its size and disease diversity. Other smaller datasets include Duke, open-access OCTID, and OCTDL. Duke dataset with 100 annotated OCT-B scans from patients with severe DME provided by Duke University (Chiu *et al.*, 2015). The open-access OCTID has more than 500 high-resolution OCT images comprising normal, MH, AMD, Central Serous Retinopathy (CSR), and Diabetic Retinopathy (DR) (Gholami *et al.*, 2020). The OCTDL has 2064 images categorised into various diseases and eye conditions (Kulyabin *et al.*, 2023). These publicly available datasets offer critical resources for developing automated diagnostic tools with real-world clinical relevance.

2.4.2 Dataset Challenges

While the availability of multiple datasets is critical, several limitations exist that limit the scalability and generalisability of OCT image classification systems. Data imbalance is a common problem, with some eye diseases like CNV overrepresented compared to rarer retinal pathologies, which can cause biases in model performance. Additionally, variability in imaging devices can cause domain shifts, making it challenging to train models on one dataset to generalise across others. Further, limited patient diversity in publicly available datasets can hinder model applicability in global populations. To address these challenges, there is a growing interest in multi-modal datasets with richer metadata and standardised imaging protocols to enhance fairness and clinical translation in OCT classification models.

2.5 Deep Learning Architectures in OCT Diagnosis

The architecture of the models used determines the success of deep learning in classifying OCT images. This section evaluates the various architectural strategies employed in OCT classification, indicating their design principles and comparative performance.

2.5.1 Custom-Built CNN Architectures

Custom-built Convolutional Neural Network (CNN) architectures are often developed for domain-specific tasks like OCT image classification. They are useful where pre-trained models may not address the subtle anatomical features, like in retinal diseases. Custom-built CNNs provide the architectural flexibility needed in integrating domain knowledge with the various layers for detecting the different features of an image. A typical CNN architecture has two parts: the convolutional base and the classifier. The convolutional base undertakes feature extraction while the classifier classifies

an image based on the detected features. CNNs are typically designed with 3 to 7 convolutional layers and employ a hierarchical feature extraction approach with low-level features learned in the initial layers and more abstract representations in the deeper layers. Several researchers have made custom CNNs to classify OCT images in eye disease diagnosis. For instance, Baba, Kumari, and Saxena (2024) proposed a custom CNN to classify OCT images of normal, CNV, DME, and Drusen from a public dataset. The proposed model achieved a training and validation accuracy of 97% and 93% respectively. It had a testing accuracy of 98% with a loss of 0.051, outperforming the other existing models in the study. Similarly, Puneet, Kumar & Gupta (2022) implemented the concept of Attention, Transfer Learning with deep learning CNN. Their model attained an accuracy of 97.79% and 95.6% on the training and testing data, respectively. The model managed to classify CNV, DME, and Drusen from the OCT images. Deepak & Bhat (2024) developed an optimised deep learning-based model using CNN for the multi-classification of ocular diseases - normal, glaucoma, and cataract. They optimised SqueezeNet, Darknet-53, and EfficientNet-b0 concerning batch size (6/8/10) and optimiser type (SGDM, RMSProp, Adam) to improve accuracy. The comparative analysis of SqueezeNet, Darknet-53, and EfficientNet-b0 gave an accuracy of 95%, 99.4% and 90%, respectively, indicating the importance of batch size and optimiser type in the performance of CNN models. However, Mikolaj *et al.* (2024) indicate that the performance of CNN models is closely tied to hyperparameter tuning and extensive experimentation, making them less attractive where scalability and robustness are required.

2.5.2 Pre-trained Models and Transfer Learning

Deep learning models typically require large-scale labelled datasets and extensive computational resources for training. In medical imaging, where data is limited, transfer learning with pre-trained models has been widely adopted. Transfer learning entails leveraging models that have been trained on large datasets like ImageNet and customising them for a given task. Some of the most common pre-trained architectures in OCT are VGG16, DenseNet121, and ResNet50. Simonyan & Zisserman (2014) proposed VGG16, a model with three fully connected and 13 convolution layers. Despite the high computational cost, VGG16 has been widely used in OCT classification because of its ease of implementation and strong baseline performance. Shourie *et al.* (2024) designed a deep learning method based on the VGG16 architecture for the identification of retinal injury using a dataset of OCT images. The dataset was used to fine-tune the pretrained VGG16 model to adjust to the unique properties of retinal images. The suggested model improved validation accuracy from 87.89% to 92.01% and training accuracy from 97.22% to 100%. ResNet50, proposed by He *et al.* (2016), is a residual learning framework to facilitate the training of networks that are deeper without degradation. Its architecture allows it to deal with everyday challenges like overfitting and gradient instability, making it useful in medical imaging tasks that have subtle variations like DME and Drusen. A study by Li *et al.* (2020) applied ResNet50 to OCT classification for retinal diseases and attained an accuracy of 97.3%. Huang *et al.* (2017) proposed DenseNet121, a model known for its skip connections. The connections allow each layer to get inputs from all preceding layers, facilitating feature reuse and minimising the number of parameters. DenseNet121 is helpful for smaller datasets where overfitting is a primary concern. A study by Kaur *et al.* (2024) used DenseNet121 to predict retinal eye disease. The model showed optimal performance with a training accuracy of 93.68% and testing accuracy of 95.87%, with a training loss and testing loss of 0.101 and 0.048 at epoch 50 with a learning rate of 50. Overall, a critical advantage of pre-trained models is their ability to generalise from a relatively small number of labelled OCT images, hence minimising the risk of overfitting. However, researchers caution against freezing too many layers, as this may limit the network's ability

to adapt to domain-specific features, with fine-tuning all the layers likely to cause catastrophic forgetting of generic features (Song *et al.*, 2025).

2.6 Evaluation Metrics in Model Performance

When evaluating the performance of deep learning models in medical image classification, it is critical to go beyond simple accuracy. Relying solely on accuracy as the performance metric in OCT image classification can be misleading and lead to adverse outcomes. This is because medical datasets, including OCT images, tend to be highly imbalanced (Hicks *et al.*, 2022). For instance, 90% of the images may be labelled as “healthy”, and only 10% as “diseased”. A model that always predicts “healthy” would still attain 90% accuracy despite failing to account for the diseased cases.

Additionally, accuracy alone can give a false sense of reliability by masking sensitivity. When the model misses actual disease instances, it amplifies the risk of a patient failing to receive treatment. As a result, key performance indicators such as precision, recall, F1-score, area under the ROC curve (AUC), and the confusion matrix should be applied alongside accuracy in OCT image classification. Precision considers the accuracy of identifying actual positive cases among the images classified as “diseased”. This is essential in medical settings where false negatives, like missed diagnoses, can lead to delayed or inappropriate treatment (Meyer *et al.*, 2021). F1 is a critical metric that demonstrates the balance between precision and recall of a diagnostic model. A high F1 score indicates a good balance between identifying positive cases and avoiding misclassifying negative cases (Jaimes *et al.*, 2025). AUC gives an aggregate measure of performance across all the classification thresholds. The metric evaluates the trade-off between sensitivity and specificity. Confusion matrices provide an interpretable summary of classification results and assist in pinpointing particular error types in diagnosis

2.7 Gaps in the Literature and Justification for the Study

While different studies have implemented deep learning for the classification of OCT images, several limitations, such as data handling, model transparency, and deployment readiness, persist. Prior models, such as those by Kermany *et al.* (2018) and Jaimes *et al.* (2025), emphasise classification accuracy. However, such models lack robustness in explainability and generalisability. Additionally, a majority of previous works overlook user accessibility and fail to address class imbalance. This research improves on existing approaches by employing a multi-tiered enhancement process. The study uses publicly available OCT images from Kaggle, allowing efficient dataset acquisition. Moreover, our approach includes dynamic data augmentation and a thorough exploration of class imbalance, all of which contribute to better generalisation. In contrast to earlier static training pipelines, our model leverages diverse architectures—including DenseNet121, ResNet50, and custom CNNs—and employs transfer learning for improved performance on limited data. This positions the work not only as more performant but also as more adaptable, interpretable, and scalable for clinical settings.

2.8 Chapter Summary

This chapter has reviewed the technological advancements in OCT-based retinal disease diagnosis, with a critical analysis of AI, deep learning architectures, and performance evaluation metrics. It has identified the limitations in the current literature, including limited accessibility, insufficient data handling, and lack of explainability. This study builds on existing models to create a more robust, transparent, and scalable diagnostic framework. The next chapter outlines the methodology used to implement and evaluate this improved approach.

Literature Summary Table

Author(s), Year	Objective/Focus	Methods/Approach	Key Findings	Limitations/Gaps	Relevance to Current Study
Chew, 2020	To investigate prevalence, incidence, and risk factors of age-related macular degeneration (AMD) in a population-based cohort	Longitudinal epidemiological study of ~5000 participants ≥43 years in Beaver Dam, Wisconsin; comprehensive eye exams and centrally graded fundus photographs	Established age as a major risk factor; identified large drusen and RPE pigmentary changes as predictors of progression; prevalence of late AMD significant by age 75	Focused on a single geographic population (predominantly White cohort), limiting generalizability; reliance on fundus photography (OCT not yet in use); limited by imaging technology of the time	Provides foundational epidemiological insights into AMD natural history; informs risk prediction models and classification schemes relevant for AI-based OCT analysis; highlights modifiable risk factors (e.g., smoking) and genetic links that future ML models may incorporate
Zhang, S., Ren, J., Chai, R., Yuan, S., & Hao, Y. (2024)	To establish the global burden of AMD-related low vision and blindness from 1990–2021, with projections to 2050	Data analysis from Global Burden of Disease (GBD 2021) study across 204 countries	The prevalent AMD-related low vision/blindness cases rose from ~3.6M (1990) to ~8.0M (2021). The burden is higher in older adults, women, and low-SDI regions There are projections of 9-14 million cases and about 640,000-760,000 DAILYs by 2050	The study relies on modeled GBD estimates which leads to overreporting and under reporting in some regions. The predictive models carry uncertainty beyond 2050	The study shows a growing global AMD burden with strong epidemiological projections It underscores the urgency for scalable and cost-effective screening solution which supports rationale for AI-OCT tools as non-invasive
Sheng et al., (2021)	Identification of novel genes	Applied a network-based	The study identified 11	Reliance on incomplete/bi	It supports the integration of AI-

	associated with CNV	approach using STRING protein-protein interaction database together with Laplacian heat diffusion algorithm with validated CNV genes as seed nodes	previously unknown genes strongly linked to CNV	used PPI networks	driven approaches in detecting biomarkers for vision-related conditions
Uchida et al., 2018	To establish OCTA for detecting CNV in eyes with indeterminate findings on conventional imaging (SD-OCT, FA)	Prospective observational study (AVATAR)	OCTA detected CNV in 28% of eyes where diagnosis was unclear	The sample size of 29 was small	Indicates the need for advanced imaging as a comparator for AI-based detection methods
Zeppieri et al., 2023	To review the technological evolution, applications, and diagnostic capabilities of OCT ophthalmology and beyond	A narrative literature review tracing OCT development from time-domain to spectral-domain and swept-source	OCT has revolutionized ophthalmic diagnosis with high-resolution and non-invasive imaging	It fails to account for challenges like accessibility and cost	Establishes OCT as a key non-invasive approach to eye disease diagnosis.
Du et al., 2023	To evaluate RETFound, a foundation model pretrained on OCT images, for automated detection of retinal disease features such as SRF, IRF, drusen, and PED	RETFound was pretrained on 1.6M unlabeled OCT images and fine-tuned using 1,770 labeled OCT B-scans	RETFound achieved accuracy (0.75–0.77) and AUC-ROC (0.75–0.80), comparable to ResNet-50, hence an improved diagnostic accuracy and interpretability	Relatively small labeled dataset (1,770 B-scans) may limit generalizability	Supports AI in improving specificity and reliability of OCT image interpretation
Falavarjani et al., 2022	To highlight how segmentation error correction	Reviewed 1,559 OCTA articles published	Only 12.57% reported manual correction;	Lack of standardized	Highlights the risk of inaccurate conclusions in OCTA-based

	in OCTA images is done in peer-reviewed studies	between 2015–2021	37.8% excluded poor-quality images; 6.3% acknowledged error as limitation; 43.3% did not address segmentation errors	correction protocols	studies, relevant when considering reliable
Avanzo et al., 2024	To establish the evolution of AI in medical imaging	Narrative review of the historical development of AI in medical imaging	AI has become increasingly tied into radiology and imaging	There is a “blackbox” interpretability of results	Offers a foundation for AI detection
Khan et al., 2021	To identify publicly available ophthalmological imaging datasets	Systematic review using MEDLINE, Google Search, and Google Dataset Search; identified and analyzed 94 datasets (507,724 images, 125 videos, 122,364 patients)	There is an overrepresentation of glaucoma, diabetic retinopathy, and AMD compared to other eye diseases in published studies	A lack of inclusivity for underrepresented groups	Shows the need for balanced, representative datasets and robust metadata standards for AI/ML in ophthalmology, aligning with goals of reducing bias and improving generalisability
Kermany et al., 2018	To develop and validate a deep learning framework for detecting common treatable retinal diseases (AMD, DME) using OCT, and extend applicability to other medical imaging domains	Applied transfer learning with OCT datasets	AI achieved diagnostic performance comparable to ophthalmology experts for AMD and DME detection	Generalizability across populations/disease types needs further testing	Demonstrates potential of deep learning in OCT-based retinal disease detection
Puneet, Kumar & Gupta, 2022	To develop an autonomous system for accurate	Applied attention mechanisms and transfer learning	Attained 97.79% accuracy on training and 95.6% on	Limited disease categories and hence requires	Provides evidence of DCNN’s potential in non-invasive

	detection of ocular diseases from OCT images using AI techniques.	with a Deep Convolutional Neural Network (DCNN) on OCT datasets	testing; demonstrated high efficiency in classifying ocular disorders	further validation on larger	ophthalmic disease detection
Simonyan & Zisserman, 2015	To investigate the effect of increasing convolutional network depth on accuracy in large-scale image recognition	A designed and tested very deep CNNs (16–19 layers) with small 3×3 $\times$ 33×3 convolutional filters;	Deeper networks significantly improved accuracy compared to prior architectures	The approach is computationally expensive	The results indicate that deeper CNN architectures enhance feature extraction. This is needed when applying CNNs to medical imaging tasks such as diabetic retinopathy detection
Li et al., 2019	Automated detection and classification of retinal diseases (CNV, DME, Drusen, Normal) using OCT images	Developed an ensemble of four improved ResNet50 models	Achieved 97.3% accuracy, 96.3% sensitivity, and 98.5% specificity at B-scan level	The database size was limited and focused only on four classes of diseases. Hence, generalizability to broader populations is limited	Demonstrates effectiveness of deep learning ensembles in retinal disease detection

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