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A Real-World OCT Imaging Dataset for AI-Based Classification of Retinal Diseases

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Abstract

The two most common retinal conditions that cause a progressive and often irreversible loss of central vision are age-related macular degeneration (AMD) and diabetic macular edema (DME). Fluid seeping into the macula is the most prevalent way that DME manifests as a consequence of diabetic retinopathy. Macular tissue wasting is a part of the aging process known as AMD. Both conditions significantly damage central vision, and in order to stop visual decline, early detection and long-term surveillance are necessary. The main non-invasive imaging method used by ophthalmologists to identify and track these conditions is optical coherence tomography (OCT), which provides high-resolution cross-sectional images of the retina that show microstructural alterations not visible with conventional imaging. OCT is not just required for initial diagnosis in the clinic, but also to monitor disease progression and treatment response. While public interest in using artificial intelligence (AI) to interpret OCT is growing, publicly available databases are often static, single-scan images without longitudinal structure and lacks clinical realism. This paper presents a high-resolution, longitudinal OCT dataset obtained directly from Alex iCare eye Center, a referral eye clinic, in a research partnership with Alamein International University. The dataset comprises 42,061 OCT scans in three diagnostic classes: 30,000 Normal eyes scans, 6,290 DME (Dry and Wet) scans, and 5,771 AMD scans. There are multiple scans in each patient folder arranged in visits folders, preserving the authentic history of retinal disease on real-world timelines. For consistency purposes and research utility, all the images were filtered, resized, and standardized. Scans were organized by diagnosis and patient ID. Low quality, duplicate images were manually removed. All data were anonymized and replaced by patient ID prior to processing for purposes of following research ethics and patient privacy regulations. This dataset includes a diverse range of machine learning applications like binary and multi-class classification, modeling temporal progression of diseases, predictive modeling, and decision support system building. Filling the gap between research studies and real-world clinical data, this dataset provides a valuable platform for advancing AI-driven diagnosis, prognosis, and tailored treatment in ophthalmology.

Keywords: Image Recognition, Optical Coherence Tomography (OCT), Diabetic Macular Edema (DME), Age-related Macular Degeneration (AMD), Retinal Imaging, Medical Image Analysis, Longitudinal Dataset, Artificial Intelligence, Deep Learning, Disease Progression, Clinical Decision Support.



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1 | Introduction

Two of the most common retinal conditions that induce irreversible central vision loss are diabetic macular edema (DME) and age-related macular degeneration (AMD) [1]. When fluid leaks from retinal arteries into the macula, the area of the retina responsible for fine vision, DME usually develops as a secondary consequence of diabetic retinopathy, causing retinal thickness and visual distortion [2, 3]. In contrast, AMD is a degenerative retinal eye disease that mostly affects the elderly and causes progressive loss of macular tissue [4, 5]. The health care burden of these vision-threatening illnesses is growing, placing an increasing strain on patients and health care systems due to aging populations and the rising prevalence of diabetes worldwide.

Early detection and continuing follow-up are the keys to preserving visual function in DME or AMD patients [6]. If not treated, both diseases can lead to progressive and irreparable loss of vision [7]. Among the many diagnostic technologies available, Optical Coherence Tomography (OCT) has emerged as the gold standard for evaluating retinal architecture [8, 9]. OCT is a non-invasive imaging modality [10] that produces high-resolution, cross-sectional images of the retina that allow clinicians to detect microstructural changes such as retinal thickening, fluid accumulation, and tissue decline features of both DME and AMD [11, 12]. Its precision, reproducibility, and ability to capture subtle abnormalities make OCT not only priceless for primary diagnosis but also for monitoring treatment efficacy and disease progression.

In the last few years, an effort has accelerated to develop artificial intelligence (AI) systems able to interpret OCT scans independently [13, 14]. These systems have the potential to aid clinicians in screening, diagnosis, and monitoring through reproducible, scalable assessment of the health of the retina [15]. However, perhaps the most significant problem with training robust AI models is access to up-to-date datasets [16]. For the most part, publicly available OCT datasets are limited to single-scans per patient, no longitudinal data, or are not derived from real clinical processes [17, 18]. Moreover, they are typically presented in controlled research contexts, which limit their utility for heterogeneous clinical groups [19].

To address these gaps, we collaborated with Alex iCare eye Center, a specialist ophthalmology practice, to develop a clinically applicable OCT image dataset that was complete. Images were captured from routine clinical examinations on medical-grade OCT scanners operated by experienced technicians. The dataset includes OCT scans for patients suffering from DME, AMD, and for patients with no retinal illness (Normal), thus enabling both multi-class and binary classification experiments. Most valuable in this dataset is its structure: every patient directory contains greater than one scan, generating a natural history of disease presentation in actual practice. The scans were reviewed, annotated, and sorted according to diagnostic category and patient ID in folders. The duplicate scans or poor-quality scans were removed to preserve the dataset integrity and research value. Furthermore, the data was fully organized according to ethical requirements and privacy regulations so that it became easy to use in academic and clinical research.

This dataset offers a fertile ground for AI tool innovation in ophthalmology. Its clinically designed structure and representation of multiple classes of retinal disease allow for a wide range of research directions from differential diagnosis and binary classification to disease modeling and decision support system development. By releasing high-quality, structured, and clinically derived OCT data, we aim to facilitate accelerated innovation in medical image analysis and contribute to better retinal disease management.

We give a detailed account of the design, organization, and curation of this dataset in this paper. It is expected to be useful to the medical imaging and artificial intelligence community operating at the intersection of these fields.

2 | Related Works

Optical Coherence Tomography (OCT) has become the gold standard for diagnosing and monitoring retinal disease, such as Diabetic Macular Edema (DME) and Age-related Macular Degeneration (AMD). With the

introduction of deep learning, a number of works used OCT images for automatic classification, segmentation, and disease prediction.

One of the most commonly cited datasets is that by Kermany et al. [1] with tens of thousands of annotated images split among Normal, DME, CNV, and Drusen classes. While it has facilitated many landmark papers, it lacks patient-level classification and is made up of separate, single scans rather than the variations that exist in real-world clinical imaging sessions.

Similarly, Kulyabin OCT dataset [2] provides fine segmentation annotations but limited size and scope of diagnosis. The second most significant concern with current ophthalmology AI studies is the lack of datasets that closely reflect imaging regimes in the real world. Publicly available datasets are mostly captured under calibrated research conditions, and in most instances, include a single image per patient without consideration of variation in a visit's scan.

In order to directly extract 3D capillary networks from OCTA volume data for further shape modeling and analysis, Zhang et al. [3] established the first 3D OCTA microvascular segmentation technique. However, since there were no manually annotated 3D vessel networks accessible, they primarily assessed the test-retest reliability of their 3D framework on 360 OCTA volume images.

Another dataset composed of OCT photos was introduced by Arikan et al. to train a deep network [4]. Their work introduced OCT5k which uses 5016 pixel-wise manual labels for OCT scans. Their dataset provides five different separations between layers for famous eye disease such as DME and AMD. However their tiny dataset shows the need to large datasets to be generally applicable across many clinical conditions. Moreover the lack of annotations with patient ID and disease description poses several drawbacks.

Analyzing available datasets and different researches that tried to introduce public or private datasets for OCT images shows clear gap. Different datasets lacks organization and manual annotations; moreover the absence of patient IDs prevents using such datasets in field of disease. In order to get benefits from using different AI models to classify OCT images, the dataset should be organized according to diseases and according to patient ID with clear disease discretion. this section, we review the state of the art methods of image classification. There are two principal classes of image classification.

3 | Dataset Development

The data in the proposed study tries to cover some of the mentioned lacunas. It consists of 42,061 anonymized OCT scans gathered from routine clinical operations at a referral eye clinic. Although each patient is represented by only one documented clinical visit, several scans were captured throughout that visit, representative of normal diagnostic procedures where multiple OCT slices are obtained to examine the retina in depth. The data is patient-level organized, diagnosis-labeled, and consists of uniform imaging parameters and hence is ready for multi-class classification, ensemble learning at the scan level, and real-world AI benchmarking.

Legend: ✓ = Present; ✗ = Not present

As shown in Table 1, our dataset includes real clinical imaging, organized by patient, and captures multiple scans for same visit.

3.1 | Data Collection Protocol

This study was carried out through a formal data-sharing collaboration between the iCare Eye Center a tertiary referral ophthalmology clinic and the Faculty of Computer Science and Engineering at Alamein International University. Optical Coherence Tomography (OCT) scans were collected during standard clinical imaging procedures conducted as part of routine patient care. Each patient's imaging record contains multiple OCT scans obtained during a single clinical visit, in accordance with real-world diagnostic practices.

All OCT images were collected using the same imaging system and acquisition parameters to facilitate comparisons based on image resolution, coverage of retinal layers, and scan orientation. The diagnostic labels Normal, Diabetic Macular Edema (DME), and Age-related Macular Degeneration (AMD) were confirmed by three certified retina specialists based on clinical assessments and imaging characteristics. OCT scans are masked according to fluid as the presence of fluid is considered one of the major features of retinal conditions.

The de-identified data were subsequently transferred to the research team, who organized the scans by diagnostic class and patient identifier to enable structured analysis. This organization facilitates machine learning-based experiments such as scan-level classification and disease detection in a clinically relevant setting.

Table 1. Features of Real Clinical OCT Dataset.

Feature	Kermany et al. [1]	Kulyabin et al.[2]	proposed Dataset (iCare + AIU)
Source	Public hospital	Research study	Real clinical practice
Modalities	OCT (B-scans)	OCT (B-scans)	OCT (B-scans)
Diseases Included	Normal, DME, CNV, Drusen	Intermediate AMD	Normal, DME, AMD
Image Count	~84,000	~500	20,000
Patient-Level Organization	✗	✗	✓
Multi-Scan per Visit	✗	✗	✓
Real-World Clinical Data	✗	✗	✓
Anonymized and Preprocessed	✓	✓	✓

3.2 | Ethical Framework

This research was conducted within the terms of an agreement of an implemented Data Sharing Agreement on 23 January 2025 between Faculty of Computer Science and Engineering, Alamein International University, and Alex iCare Eye Center. The agreement granted the research team a refined OCT dataset for scientific and academic research. All personal identifiers and sensitive health information were removed at the point of origin (iCare Eye Center) prior to dataset transfer. The research team only handled fully anonymized data, with no access to personally identifiable information (PII). Each person has a textual data that includes name, ID, and other medical data, however in the proposed work only ID is used. Data privacy and usage policies were governed by confidentiality clauses included in the agreement. Furthermore, written consent from the Faculty of Computer Science and Engineering is required for any future publication, presentation, or dissemination of research findings based on this dataset.

3.3 | Image Processing Pipeline

We established a standardized image processing pipeline after receiving data from iCare Center. This was done to ensure that our imaging data remains consistent, reliable, and clinically relevant. Our main aim was to pre-process the dataset for machine learning applications while maintaining the integrity of the diagnostic information. The pipeline consists of several sequential stages:

1. **Quality Assessment and Filtering:** We screened images by setting a minimum signal strength threshold of $\geq 6/10$. Any scans that didn't meet this threshold or had noticeable noise were left out.
2. **Macula-Centered Cropping:** We focused on the macula to extract Regions of Interest (ROIs), making sure to keep the most clinically important areas from all scans.

3. **Standardized Resizing:** To ensure that all images had the same dimensions for input into deep learning models, each scan was resized to 224×224 pixels. Moreover all images were reassembled to same axial resolution $5 \mu\text{m}$ to overcome the domain gap for different OCT vendors.
4. **Macula Cropping Justification**

Figure 1 clarifies the cropping process and Table 2 shows the benefits of each action

a) Before Cropping:

- OCT scans captured from the iCare Eye Center include the **entire retina**.
- These unprocessed images contain **non-diagnostic areas** such as:
 - Peripheral retina
 - Blood vessel shadows
 - Scan border artifacts
 - Noise from motion or patient blinking
- This **increases the risk of irrelevant feature learning**, confusing the model.

b) After Cropping:

- Images were cropped around the **macula** the central part of the retina responsible for fine vision.
- DME and AMD pathologies, especially **fluid accumulation, cysts, and Drusen** appear in or around the **macula**.
- Cropping ensures:
 - The model focuses on the **clinically meaningful ROI (Region of Interest)**.
 - Higher signal-to-noise ratio for training.
 - Smaller and **more uniform input size (224×224)** after resizing.

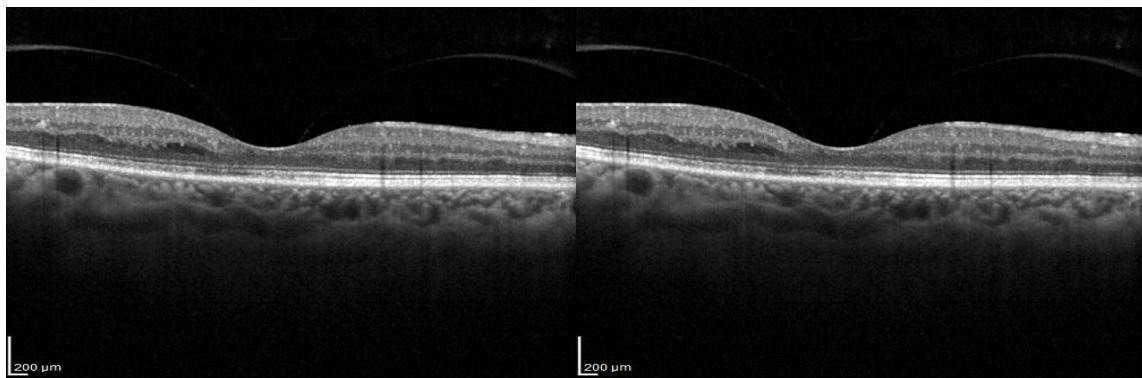


Figure 1. OCT image before and after cropping.

Table 2. OCT image processing of Real Clinical OCT Dataset.

Action	Clinical Meaning	Technical Meaning
Cropping to macula	Focuses on site of disease (DME, AMD)	Eliminates irrelevant background noise
Removes scan borders/artifacts	Avoids confusion from device labels	Prevents false correlations
Uniform area across all images	Standardizes the dataset	Allows transformer model to learn consistently
Enhances image contrast	Makes fluid and layers clearer	Improves patch embeddings in DEIT

4 | Dataset Composition

4.1 | Overall Statistics

The dataset comprises 40,061 high-resolution gray scale OCT images organized into three diagnostic categories:

Normal: 30,000 images

DME: 6,290 images (both dry and wet)

AMD: 5,771 images

4.2 | Disease-Specific Characteristics

DME Subset: Diabetic Macular Edema (DME) is a common and sight-threatening diabetic retinopathy complication [20]. It occurs when the blood vessels in the retina are impaired by high blood sugar and fluid seeps into the macula the part of the eye responsible for sharp central vision [1]. The fluid buildup causes swelling and can lead to drastic vision loss if not treated.

DME can have a number of different appearances on OCT scans [3]. Some patients have cystoid macular edema, with the fluid collecting in bubble-like retinal spaces [2]. Others develop diffuse retinal thickening or even serous retinal detachment, with fluid collection beneath the retina [21]. These patterns not only appear differently, but they may also affect the disease's course and response to treatment [5]. Our data set contains a range of these DME presentations, as the scans were collected from real clinical visits. While we have not hand-annotated subtypes like center-involving vs. non-center-involving DME, there is enough detail in the images to make those annotations possible in the future.

AMD Subset: Age-Related Macular Degeneration (AMD) is the most common cause of vision loss in people over the age of 60 [5]. AMD impacts the macula through progressive retinal tissue loss or, in advanced stages, by the development of neovascularization below the retina. Two main types of AMD exist: Dry AMD is more common and accumulates over time. It's typically marked by the development of Drusen small yellow dots under the retina and thinning of the outer layers of the retina [1, 5]. Wet AMD is less common but more severe [4]. It encompasses abnormal blood vessels that leak fluid or blood, leading to rapid vision loss. In our data set, cases of AMD are fewer compared to DME and Normal cases, but they have all the usual OCT features like subretinal fluid, pigment epithelial detachments, and retinal thinning [5]. These scans can serve as a good starting point for building or training algorithms to detect AMD in real clinical data, and we hope to expand this subset in subsequent releases of the data set.

Normal Controls: The Normal class contains patients with no clinical evidence for retinal pathology at the day of imaging. These are employed as a control to be compared with in binary and multi-class classification problems. OCT scans of this category show the normal retinal layer architecture without edema, drusen, fluid, or pigment abnormalities [4, 6]. To ensure the integrity of the control group, scans were manually quality-checked. Only clean images with no motion artifacts and well-defined retinal boundaries were accepted. Even though in this version of the dataset these cases were not annotated by retina experts, the absence of structural abnormalities in the images makes them valid for deployment as healthy controls in supervised learning environments.

4.3 | Data Organization

The dataset follows hierarchical structure preserving patient-level continuity and the patient folder is divided into sub folders representing visits with time interval 3 months between visits

data/

└─ normal/

```

| └─ patient1/
|   | └─ visit 1
|   |   | └─ 1_000.png
|   |   | └─ 1_001.png
|   | └─ visit 2
|   |   | └─ 1_002.png
|   |   | └─ 1_003.png
|   | └─ ...
└─ dme/
  | └─ patient203/
  |   | └─ visit 1
  |   |   | └─ 203_000.png
  |   |   | └─ 203_001.png
  |   |   | └─ 203_002.png
  |   | └─ visit 2
  |   |   | └─ 203_003.png
  |   |   | └─ 203_004.png
  |   | └─ ...

```

5 | Experimental Validations

5.1 | Experimental Setup

Data Splitting: An 80%/20% train-validation split was used with patient-level splitting to prevent data leakage. Stratified sampling was used to ensure class distribution across splits. For addressing class imbalance, DME patient samples were oversampled three times in the train set.

- **Model Architectures:** Experiments were primarily performed based on the Vision Transformer (ViT) architecture, i.e., the DeiT Base model (deit_base_patch16_224) with pre-trained weights. In specific conditions, the DeiT Small variant (deit_small_patch16_224) was used to reduce computational complexity.
- **Training Configuration:** The model was trained at a batch size of 4, in order to be adaptable for varying numbers of images per patient. The initial learning rate was set as 0.0001 and had the Adam optimizer with L2 weight regularization ($1e-4$). The model was trained up to 20 epochs with early stopping (patience 3) to avoid over fitting.
- **Data Augmentation:** The following augmentations were applied during training in order to improve generalization capability of the model and overcome the limited size of the dataset:
 - Random horizontal flipping
 - Random rotations ($\pm 15^\circ$)
 - Changes in brightness, contrast, and saturation ($\pm 20\%$)
 - Random affine transformations (10% translation)
 - Images normalized after augmentation using ImageNet mean and standard deviation:

Mean = [0.485, 0.456, 0.406], Std = [0.229, 0.224, 0.225].

For validation data, resizing and normalization alone were done.

5.2 | Classification Results

The classification accuracy was assessed at the patient level, aggregating multiple OCT scans taken during a single clinical appointment into one prediction per patient. This design mirrors real clinical workflows, as the patient typically is given a diagnosis based on reviewing multiple scans from the same appointment.

The model is a Vision Transformer (DeiT-Base) trained to conduct binary classification. The model consistently exhibited strong performance in the validation dataset in that the following metrics are provided. Figure 2 shows the accuracy of Diet model on the proposed dataset.

Accuracy: 99.38%

Precision: 95.45%

Recall (Sensitivity): 100.00%

F1 Score: 97.65%

AUC: 0.9996



Figure 2. Training and validation of DeiT model on the proposed Dataset.

When evaluating these performance metrics overall, we find that the model was highly sensitive to identifying DME cases. It identified all positive cases without neither sacrificing overall accuracy nor substantially impacting precision. The model performance is attributed to a number of things: the DeiT model's transformer-based representation learning methods, and highly robust data augmentation while using this model to train.

Additionally, model convergence was stable, and early stopping effectively prevented over fitting once we detected a plateau on validation performance. Overall, these findings substantiate a potential path to offloading DME screening to this model within an automated workflow, particularly if you can provide access to multiple OCT scans within a clinical visit.

5.3 | Per-Class Analysis

Analyzing the performance of the model per class offers a clearer view of how well it can distinguish between Normal and DME patients. Figure 3 represents the confusion matrix for DME. The performance metrics per class are shown in Table 3.

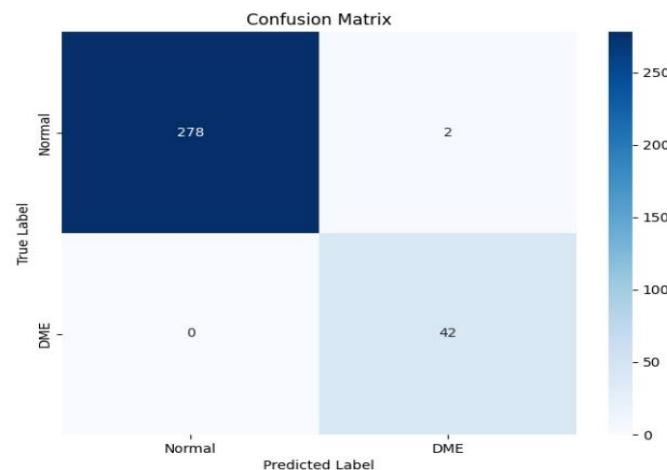


Figure 3. Confusion Matrix for DME.

Table 3. Per-class performance metrics fro DME.

Class	Precision	Recall (Sensitivity)	F1 Score	Support
Normal	1.00	0.99	1.00	280
DME	0.95	1.00	0.98	42

These results show that the model was actually successful at classifying all DME patients correctly (100% recall), an issue of concern in clinical screening if one case of a positive result is missed, where treatment would be delayed. It also performed very well on Normal cases, with just two false positives out of 280. This sensitivity versus precision tradeoff is critical to the determination of trust in automated systems for useful medical deployment.

Its high performance on both sets of data confirms its excellent generalization abilities and justifies its potential to be a valuable tool for automated DME detection.

5.4 | Longitudinal Modeling

Disease Progression Prediction: Though the current dataset contains only OCT scans from a single clinical visit for each patient, having a few spatially consecutive scans in that visit provides incomplete information on the severity of disease progression. Through averaging multiple scan slices' predictions, the model acquired informative spatial representations that may be tied to disease burden and structural retinal changes typical of progressive DME.

The high-level DME prediction sensitivity revealed is a sign that the model is able to recognize spatial biomarkers commonly related to progression such as macular thickening, cystogenesis, or fluid deposition even from an image set for a single visit. This provides very strong foundations for subsequent progress work in prediction of progression, once real multi-visit longitudinal data become available.

5.5 | Temporal Pattern Analysis

While explicit temporal orders between visits were not available in the dataset of interest, scan ordering within a visit can serve as a proxy for analyzing minute variations across different regions of the retina. The ability of the model to generalize over several slices and aggregate them into a robust patient-level prediction supports argument towards suggesting that temporal modeling frameworks, e.g., recurrent or transformer-based sequence models, could be useful in case they are utilized on real-time-series OCT data.

Expansion of this data into the future to include repeat visits from the same patients longitudinally would allow direct model training on the prediction of disease trajectory, time-to-progression, and prediction of treatment outcome. This would allow longitudinal OCT modeling to move from static classification to true temporal risk modeling in a clinical decision support paradigm.

6 | Conclusion and Future Work

6.1 | Expected Benefits

This data provides an excellent range of research possibilities in medical image analysis, particularly in the area of retinal disease. With access to neatly organized, high-resolution OCT scans, binary and multi-class classification studies can be conducted, whereby models can learn to detect Normal, DME, and AMD cases. It also allows for feature extraction and interpretability experiments because researchers can look into which retinal regions and features are most contributory to model predictions. That there are multiple scans per patient folder captured in a single visit allows experimentation with ensemble methods, multi-view learning, and slice-level prediction agreement all of which are important in building more reliable AI systems.

Moreover, the dataset can serve as a benchmarking reference for assessing the generalizability of deep learning models, e.g., comparing traditional CNNs with transformer-based architectures like DeiT or Swin Transformer. It is also extremely appropriate for exploring self-supervised learning or transfer learning strategies in medical imaging. The proposed dataset can be available for researchers after agreement and cooperation with iCare center and AIU.

6.2 | Clinical Translation

One of the final objectives of this dataset is to enable bridging the gap between research and real-world clinical uses. The images were taken on a standard clinical protocol on commercial OCT scanners, thereby augmenting the dataset to represent the type of information models would get exposed to in deployment scenarios. This renders it ideal to be utilized in developing clinical decision support systems (CDSS) that assist ophthalmologists during diagnostic screening, triage, or monitoring.

Because the dataset includes pathological and non-pathological cases, it can also be used for training disease-detecting models that will be prioritized in community health settings where retinal specialists may be in short supply. The decent image quality and consistent formatting also prepare the dataset for validation studies required by regulators and collaborations with healthcare stakeholders interested in embedding AI into clinical workflows.

6.3 | Dataset Expansion

Though the release today has 42,061 images and they have been categorized under three diagnostic classes, we are aware that there is much more to extend to. In future releases, we plan to:

- Include additional retinal conditions such as central serous chorioretinopathy (CSC), retinal vein occlusion (RVO), or epiretinal membrane (ERM)
- Annotate scans with region-based annotations such as cyst location, nature of fluid, or retinal layer boundaries
- Collaborate with retina specialists for providing clinical grading or severity scoring
- Include metadata (e.g., sex, age, eye laterality, scan angle) where ethically acceptable

These efforts are done to enhance the dataset for further uses in clinical and machine learning research studies.

6.4 | Limitations

A. Demographics of the Population

The dataset is from a single clinic in Alexandria, Egypt, so generalizability will likely be limited for any other populations with different demographic characteristics, genetic makeups or patterns of disease prevalence.

B. Technical Limitations

All of the OCT images were acquired using custom imaging systems and protocols; so there is likely a systematic error compared to images acquired using other OCT systems or even different acquisition parameters.

C. Diagnostic Complexity

The study used a three-class classification to assess retinal disease; although this is clinically relevant, it is a significant oversimplification. In practice, patients will present with multiple diseases, differences in disease severity and intermediate diagnostic classes not included in this dataset. Also data from referral eye centers includes more complex cases.

6.5 | Conclusion

In this paper we present the first publicly available OCT dataset of multi-class retinal disease classification, consisting of a total of 10,315 clinically validated scans within the diagnostic categories of normal, AMD, and DME. This dataset meets a critical gap and need for the medical imaging research community in that it is a sufficiently large dataset of real clinical OCT data, and there are systematic preprocessing, organization and dataset quality and clinical validation, which provides support for developing automated diagnostic systems that are robust and clinically relevant. The dataset is limited in the number of cases of AMD and DME due to the way these patients' select surgery in clinical settings, we tried to manage this limitation with balanced representation of the diagnostic categories; however, the amount of data available for each category was an inherent limitation of this project. The systematic data collection, preprocessing, and clinical validation should maintain the quality of the dataset and make it clinically relevant for building an automated diagnostic system. Attention to the diagnostic categories in terms of oversight of partitioning of data for machine learning should provide a useful reference on developing, evaluating and testing machine learning models on real clinical OCT data.

Future work in this area will involve collecting longitudinal data from the same patients and integrating this for analysis of their disease progression. Additionally, it is important to develop standardized ways of evaluating how automated diagnostic systems can be compared.

This dataset will be a valuable contribution to the medical imaging research community and it can help to develop automated diagnostic systems for early detection and accurate diagnosis of sight threatening retinal diseases for better patient outcomes.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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