Detection and Retinal Pathology Analysis of Early to Intermediate AMD and Chronic DME in OCT Scans Using Convolutional Neural Networks and You Only Look Once

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Abstract: ***Purpose: Diabetes can lead to complications such as diabetic nephropathy, diabetic neuropathy, and diabetic macular edema (DME). Like DME, AMD-related vision loss can also be prevented through early detection and prompt treatment. Optical coherence tomography (OCT) is the most widely used imaging technique in ophthalmology for diagnosing these conditions. While OCT is effective for early screening, the increasing volume of OCT scans adds to the workload of ophthalmologists, who must interpret each image.***

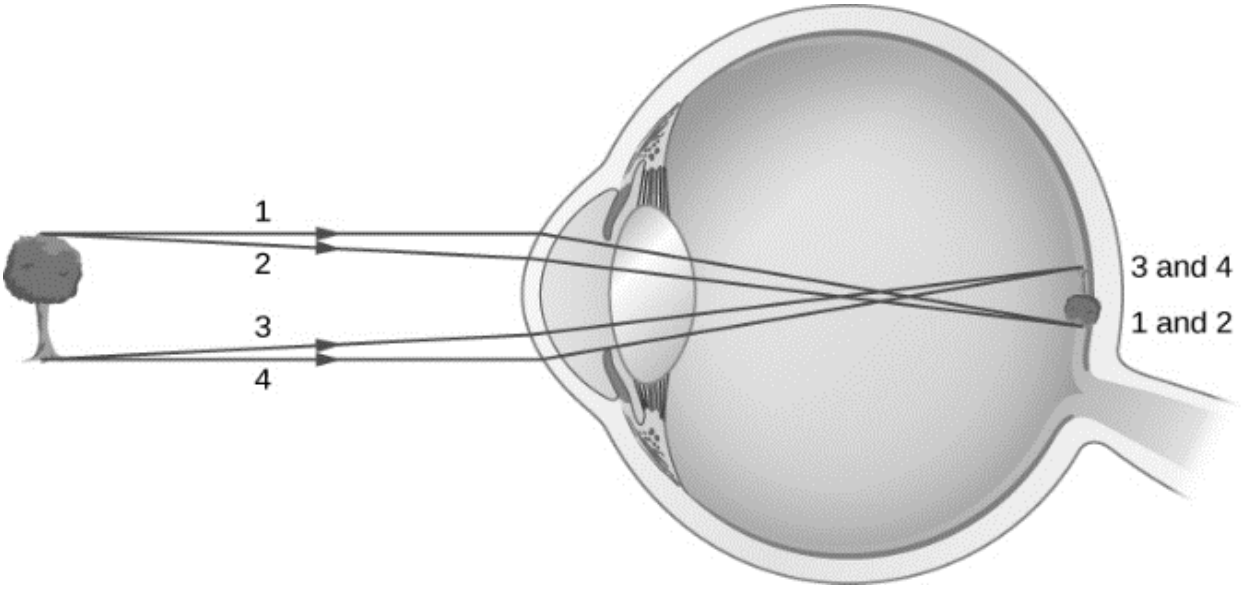
Method: To address this challenge, automated diagnostic screening systems are being actively developed to reduce the burden on eye care professionals. Prolonged diabetic may lead to Macular Edema (DME) or CNV or DRUSEN. Which causes the aberrant development of blood vessels from the choroid layer into the retina. DME, CNV may cause to vision loss. Early detection of the disease and correct treatment are crucial to address the issue of vision loss. Artificial intelligence techniques have been widely adopted in many research work to overcome these limitations. This paper contributes towards development of textual reports, helpful for ophthalmologists.

Result and Conclusion: This is the review developed for detecting and analysing DME, DRUSEN CNV using AI techniques over the last decade. Also, we tried to convert the OCT finding into a textual report, very well assessed by ophthalmologist. The system automates the process of analysing OCT images, eliminating the need for manual interpretation by ophthalmologists. This significantly reduces the time required for diagnosis. The system processes the images and generates textual reports using deep learning methods.

Index-Terms: Retinal Pathology, age-related macular degeneration, Optical coherence tomograph, Convolutional Neural Network, diabetic macular edema.

I. INTRODUCTION

This invention presents a system for translating retinal optical coherence tomography (OCT) images into diagnostic text. The system comprises an image acquisition component configured to receive OCT images of a patient's retina.



[Fig 1]

Figure 1 shows the image formation done by eye. It captures the object through the eye cornia and the rays are passed up to the retina for formation of the image at retina. Retina passes the signals to the brain via its optical nerves. The system further comprises an image preprocessing component configured to normalize the received OCT images to standardize pixel intensity values, apply noise reduction filters to enhance image clarity, and segment retinal layers to isolate regions of interest. The system also includes a feature extraction component configured to identify and quantify structural abnormalities within the segmented retinal layers. The system further comprises a deep learning classification component comprising a trained convolutional neural network configured to analyze the preprocessed OCT images and extracted features, detect and classify retinal pathologies including diabetic macular edema, drusen, and choroidal neovascularization, and determine severity levels of identified pathologies based on predefined clinical criteria. The system also includes a natural language generation component configured to convert the classification results and quantitative measurements into structured diagnostic statements, organize the diagnostic statements into a coherent clinical report following standardized reporting protocols, and incorporate relevant clinical terminology consistent with ophthalmological practice. The system further comprises an output interface component configured to display the generated diagnostic text report to a clinician. The system reduces interpretation time and human error associated with manual OCT image analysis while maintaining diagnostic accuracy.

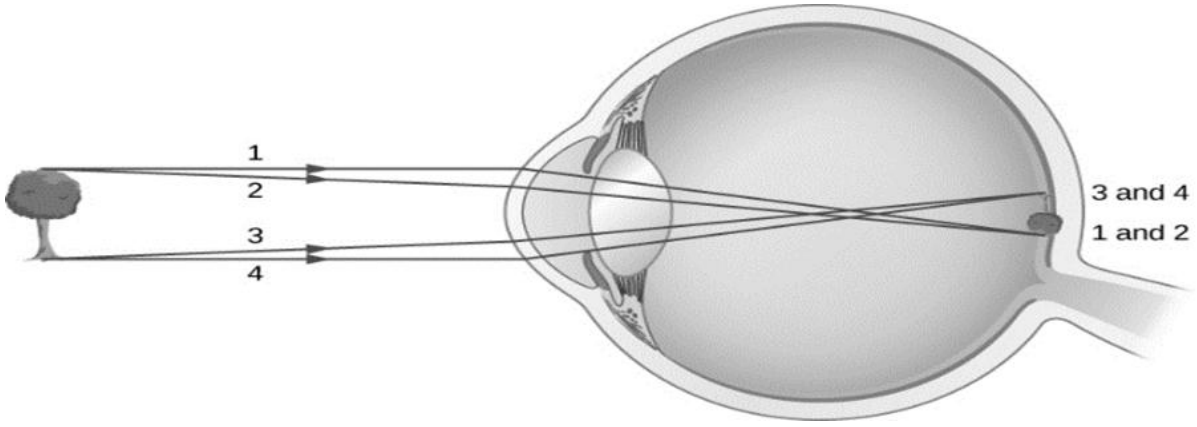
II. MATERIAL AND METHODS

State of Art

Diabetic macular edema (DME) and age-related macular degeneration (AMD), are the leading causes of blindness, primarily focusing on the use of optical coherence tomography (OCT) and artificial intelligence (AI) in their diagnosis, monitoring, and treatment.[1] Diabetic Macular Edema (DME): DME is acute, vision-threatening complication of diabetes mellitus (DM) and the main cause of vision loss in DM patients, with its global burden expected to reach 200 million people by 2040. Timely recognition and treatment can prevent its consequences on visual function. Fluid deposits in the retinal layers, which cause progressive visual loss, are a hallmark of DME. Three DME types—Cystoid Macular Edema (CME), Diffuse Retinal Thickening (DRT), and Serous Retinal Detachment (SRD)—are defined by clinical literature according to fluid accumulation. Research has contrasted DME treatments: Over the course of a year, 0.5 mg ranibizumab and 8 mg triamcinolone were compared. After a year, ranibizumab improved visual acuity ($p = 0.015$), although edema reduction was comparable across groups ($p = 0.426$). Therapy had a greater effect on fluid accumulation in the inner nuclear layer (INL) and subretinal space than it did in the outer nuclear layer (ONL). Both treatments worked and were safe. [2], [3] Anti-VEGF intravitreal is considered the gold standard for center-involving DME, while intravitreal steroid treatment is a second-line option Morphological biomarkers visible in OCT can predict treatment response and guide decisions, especially for patients who do not adequately respond to anti-VEGF therapy. [4], [5] A good response to steroids over anti-VEGF is suggested by symptoms such as a reduced choroidal vascular index, disruption of the outer retinal layers, intraretinal cysts spreading into the outer retina, and substantial volumes of retinal and choroidal hyperreflective foci.In eyes that have received successful anti-VEGF therapy, OCT biomarkers such as the presence of disruption of the inner retinal layers (DRIL), the appearance of the external limiting membrane (ELM), and the thicknesses of the inner and outer retina at the fovea and parafovea can indicate sustained visual improvements. OCT quantitative biomarkers (e.g., macular volume, central macular thickness) showed significantly greater values in T2DM, although systemic and laboratory biomarkers were more severely damaged in T1DM, according to a study comparing DME patients with Type 1 DM (T1DM) and Type 2 DM (T2DM). [6] Age-related Macular Degeneration (AMD): AMD is the one of the main cause of acute visual loss in people aged 50 or older in the world, and the leading cause of nonreversible visual dysfunction in individuals. [7],[8] Patients with AMD are classified as having early stage disease or late AMD (either "wet" neovascular AMD, "dry" atrophic AMD, or both). Anti-angiogenic drugs are a significant advancement in the treatment of neovascular AMD, providing hope for visual recovery. However, there are currently no treatments available to help eyes with advanced atrophic AMD regain their lost vision. The AREDS/AREDS2 formulation of oral supplements can lower the chance of developing advanced AMD, particularly the neovascular form. Complement-based treatment methods are being pursued as a result of recent results that link complement genes to hereditary risk for AMD. [9] Anti-amyloid treatments, autophagy regulation, and oxidative stress reduction are further possible tactics. AI with Optical Coherence Tomography (OCT) in Ophthalmology:

OCT has become a vital imaging technique for AMD and DME diagnosis and management. It makes it possible to image the retina in high resolution at the macula and optic nerve head. Automatic segmentation techniques are essential since manual retinal layer segmentation is laborious and biased. Numerous studies provide automated techniques for AI-based classification and segmentation: With high accuracy (e.g., 94% for DME, 97% for nAMD), a deep learning (DL) model can categorize ME from OCT images as normal or determine its origin among DME, neovascular AMD (nAMD), and retinal vein occlusion (RVO). [10] Especially in places where there is a dearth of specialists, this method can maximize the speed and efficiency of diagnoses, enhancing patient access and clinical decision-making. The detection of CME (84.04%), DRT (78.44%), and SRD (95.40%) was accomplished with good average accuracy using a method based on independent image areas analysis. [1], [11] A support vector machine (SVM) classifier and multiscale histograms of directed gradient descriptors were used in an automated system that detected dry AMD and DME cases from OCT volumetric scans with 100% accuracy. [12] This remote diagnosis technique has the potential to be significant. For any of the nine boundaries, a random forest classifier can reliably segment eight retinal layers in macular cube pictures with an accuracy of at least 4.3 microns. Accuracy in RPE cell segmentation is demonstrated by extending segmentation to closed-contour features such as cells and cysts using a generalized framework that combines graph theory and dynamic programming (GTDP). For the whole retina and the majority of intraretinal layers, retinal thickness measurements using programs like OCTRIMA have been shown to have good reliability and reproducibility. The topographic distribution of normal and abnormal retinal pigment epithelium (RPE) and RPE drusen complex (RPEDC) thicknesses can be used to create quantitative indications for intermediate AMD using SD-OCT. These indicators were used to create automated classifiers that demonstrated great accuracy (>0.99 AUC) in differentiating AMD from healthy eyes. [13], [14] Clinical medicine is anticipated to be significantly impacted by artificial intelligence (AI), a field of computer science that creates algorithms to mimic human intelligence. The effectiveness of new treatments depends on early identification, disease type, and illness progression prediction, all of which are quickly evolving as a result of enhanced imaging modalities and functional tests.

Proposed system using Roboflow Model:



[Fig 2]

Figure 2 shows the comprehensive model divided into two sections. The system utilizes sophisticated image processing techniques to enhance image quality and address issues such as noise and artefacts. Data augmentation methods are applied to normalize the size and diversity of training data, improving the system and ability to generalize to unseen images. Feature Extraction and Selection: The system uses algorithms to extract relevant features from OCT images, focusing on those most indicative of specific retinal diseases. This feature selection process helps to improve the accuracy and efficiency of the diagnostic process.

Integration with Existing Systems: The system is designed to integrate with existing clinical workflows and electronic health record systems, ensuring seamless adoption and utilization in healthcare settings. While the sources do not explicitly state this, you may want to verify independently that the system is designed to be user-friendly and accessible to healthcare providers with varying levels of technical expertise.

Optical Coherence Tomography (OCT) is an imaging technique which gives high-resolution and cross-sectional images of the retina. It is essential to ophthalmology because it enables doctors to see the layers of the retina and identify a range of eye diseases, including glaucoma, diabetic retinopathy and age-related macular degeneration. OCT is a vital tool for the early diagnosis and monitoring of eye illnesses due to its capacity to detect small changes in retinal structure, which can have a substantial impact on patient outcomes]. OCT picture interpretation is time-consuming and needs specialist knowledge, which might delay diagnosis and treatment even though it is a successful method. Research into machine learning and image-to-text translation techniques is necessary because of the complexity and volume of data generated by OCT scans, which call for sophisticated automated analysis tools. These techniques can help clinicians make better decisions more quickly and rapidly.

Proposed Model: The image illustrates the architecture of a Convolutional Neural Network (CNN) model used for image classification and identification tasks. The model processes an input image of size 1024×1024 through several stages:

1. Input Layer: Accepts an RGB image with dimensions 1024×1024
2. Convolutional Layers: The input's spatial information are extracted via a sequence of convolutional layers. To add non-linearity, a Rectified Linear Unit (ReLU) activation function comes after each convolutional layer.
3. Pooling Layers: To minimize computational complexity and spatial dimensions while maintaining significant features, max-pooling layers are applied sporadically.
4. Flatten Layer: To get it ready for fully connected layers, the convolutional block's final output is flattened into a one-dimensional vector.
5. Fully Connected (Dense) Layers: The flattened vector passes through one or more dense layers. Dropout layers are added in between to prevent overfitting by randomly deactivating neurons during training.
6. Output Layer: The model may make a prediction using the learned features thanks to the generation of class probabilities by a final dense layer with a softmax activation function.

This architecture is typically employed for tasks involving image recognition and classification, leveraging convolutional layers for feature extraction and dense layers for decision making.

Mathematical Model Representation

Let:

- $I \in \mathbb{R}^{H \times W \times 3}$: input OCT image of height H, width W
- $\mathcal{F}_\theta$: deep neural network with parameters θ, trained via Roboflow
- $\mathcal{P} = \{(b_i, c_i, s_i, M_i)\}_{i=1}^{N}$: output predictions, where:
  - $b_i = (x_i, y_i, w_i, h_i)$: bounding box for object i
  - $c_i \in \mathcal{C}$: predicted class label (e.g., CNV, DME, DRUSEN)
  - $s_i \in [0, 1]$: confidence score
  - $M_i \in \{0, 1\}^{H \times W}$: binary mask (segmentation)

1. Feature Extraction

$$F = \phi(I; \theta_{\text{backbone}})$$

- ϕ: backbone CNN (e.g., ResNet, EfficientNet) extracts spatial feature maps from the image.

2. Region Proposal / Detection

$$R = \psi(F; \theta_{\text{head}})$$

- Proposes object regions $R = \{r_1, r_2, \ldots, r_n\}$, each with:
  - bounding box b_i
  - classification score s_i
  - class label c_i

3. Segmentation Mask (for instance segmentation)

For each detected region:

$$M_i = \sigma(\eta(F|_{r_i}; \theta_{\text{mask}}))$$

- Crop feature map to region r_i, apply segmentation head η
- σ: sigmoid function for binary mask output
- Result is a mask M_i per instance

4. Loss Function During Training
Training minimizes a combined loss:

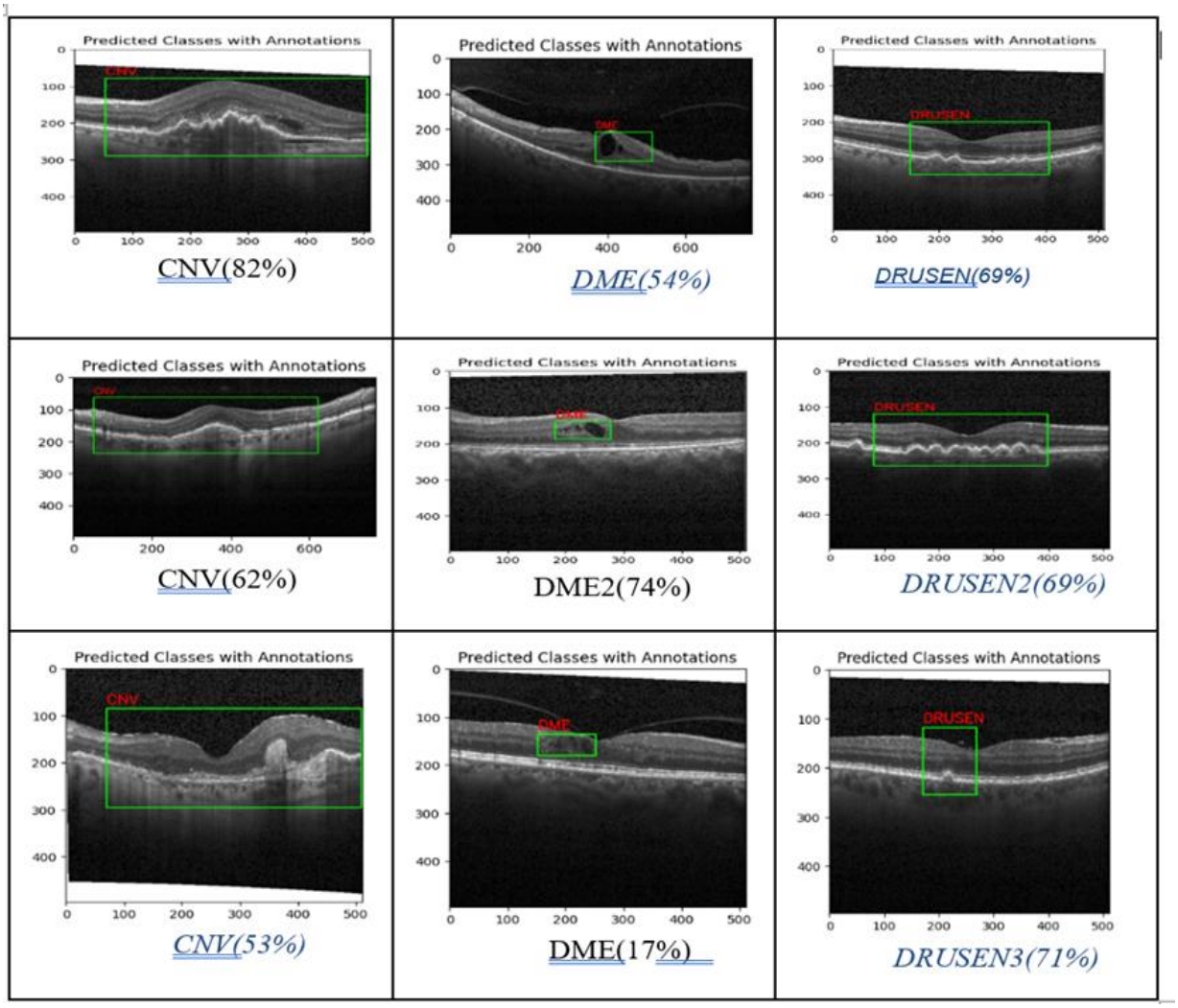
$$\mathcal{L} = \mathcal{L}_{\text{cls}} + \mathcal{L}_{\text{box}} + \mathcal{L}_{\text{mask}}$$

- $\mathcal{L}_{\text{cls}}$: classification loss (e.g., cross-entropy)
- $\mathcal{L}_{\text{box}}$: bounding box regression loss (e.g., smooth L1)
- $\mathcal{L}_{\text{mask}}$: segmentation loss (e.g., binary cross-entropy)

5. Final Prediction
The model outputs:

$$\mathcal{P} = \mathcal{F}_\theta(I) = \{(b_i, c_i, s_i, M_i)\}_{i=1}^{N}$$

3. Result & Discussion:



[Fig 3]

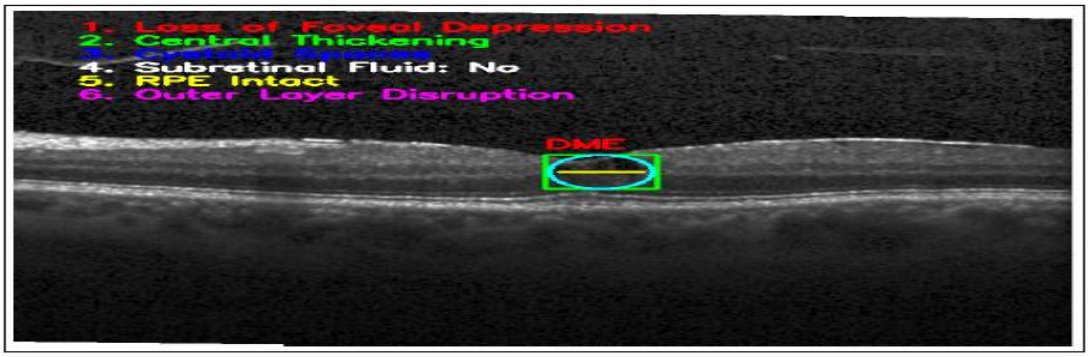
OCT report in text format

OCT Report - Diabetic Macular Edema
Patient ID: uuu
Eye: OD
Date of Examination: 2025-05-15

Model Version: 11
Confidence Threshold: 20.0%
Image Path: /content/drive/MyDrive/phd_data/OCT2017/Retina.AI/Retina.AI/DME-11053-1.jpeg
Output Image: /content/drive/MyDrive/phd_data/reports/annotated_uuu.png
1. Class: DME, Confidence: 0.87

OCT Findings:
1. Retinal architecture shows loss of foveal depression: Yes
2. Central retinal thickening observed: Yes
3. Multiple hyporeflective intraretinal cystoid spaces present: Yes
4. Subretinal fluid observed: No
5. Retinal pigment epithelium (RPE) intact: Yes
6. Outer retinal layers show structural disruption: Yes

Impression:
Findings are consistent with Diabetic Macular Edema (DME).
Characterized by cystoid macular changes and retinal thickening.
No signs of subretinal neovascularization or drusenoid deposits are present.



[Fig 4]

CNV: Eye Scan Report – Left Eye
Patient ID: aaa1
Date of Scan: May 6, 2025
What the scan shows:

- The centre of the retina (called the fovea) doesn't have its normal smooth shape. It's raised and uneven.
- A layer at the back of the eye (called the RPE) is uneven and slightly lifted in some spots.
- There is some unusual material seen underneath this layer, which suggests the growth of abnormal blood vessels.
- These new blood vessels are called choroidal neovascularization (CNV). They're not supposed to be there.
- There is fluid both inside and under the retina, which means the area is leaking—this is a sign that the CNV is active.

- Some of the leaked material is also visible under the retina, confirming that the problem is ongoing.
- A part of the retina that helps with clear vision (the ellipsoid zone) is damaged above the area with abnormal vessels.
- The retina in this area is also thicker than usual.

What this means:
The scan reveals that the left eye has an active case of wet age-related macular degeneration (AMD). If left untreated, this disorder, in which aberrant blood vessels proliferate beneath the retina and leak fluid or blood, can cause blindness.
Recommended action: Treatment with special injections called anti-VEGF may help stop or slow down the damage.

DME: Eye Scan Report – Left Eye
Patient ID: bbb1
Date of Scan: May 6, 2025
What the scan shows:

- The center of the retina (called the fovea) normally has a dip or depression. In this scan, that dip is missing, which means the retina is swollen.
- The retina in the central area is thicker than normal, a common sign of fluid buildup.
- There are several small, dark fluid-filled spaces inside the retina—these are signs of swelling.
- No fluid was found under the retina, which is a good sign.
- A deeper layer of the retina called the RPE is still healthy and undamaged.
- However, the outer layers of the retina (important for vision) are somewhat damaged.

What this means:
The scan shows Diabetic Macular Edema (DME) in the left eye. This condition happens when diabetes causes fluid to leak into the retina, leading to swelling and blurry vision.
The swelling is mainly inside the retina, and while there is some damage to the outer parts, there's no sign of bleeding or other serious changes under the retina.
Next steps: This condition can be managed with treatments like special eye injections, laser, or improving blood sugar control. Regular follow-up is important to protect vision.

DRUSEN: Eye Scan Report – Right Eye
Patient ID: ccc1
Date of Scan: May 7, 2025
What the scan shows:

- The retina was clearly visible in the scan.
- The central area of the retina is also called as fovea looks mostly normal but has a slightly uneven shape.

- There are small bumps under a layer of the retina called the RPE—these are called drusen. Drusen are deposits that can build up with age.
- There's no fluid or swelling under the retina, and no signs that the RPE layer is coming loose.
- A part of the retina involved in sharp vision (the ellipsoid zone) has mild damage right where the drusen are.
- The parts of the retina responsible for detecting light (photoreceptors) are still mostly healthy in the centre.
- The inner parts of the retina look normal, and there's no swelling or cysts inside the retina.
- No signs of bleeding, leaking blood vessels, or serious complications were seen.

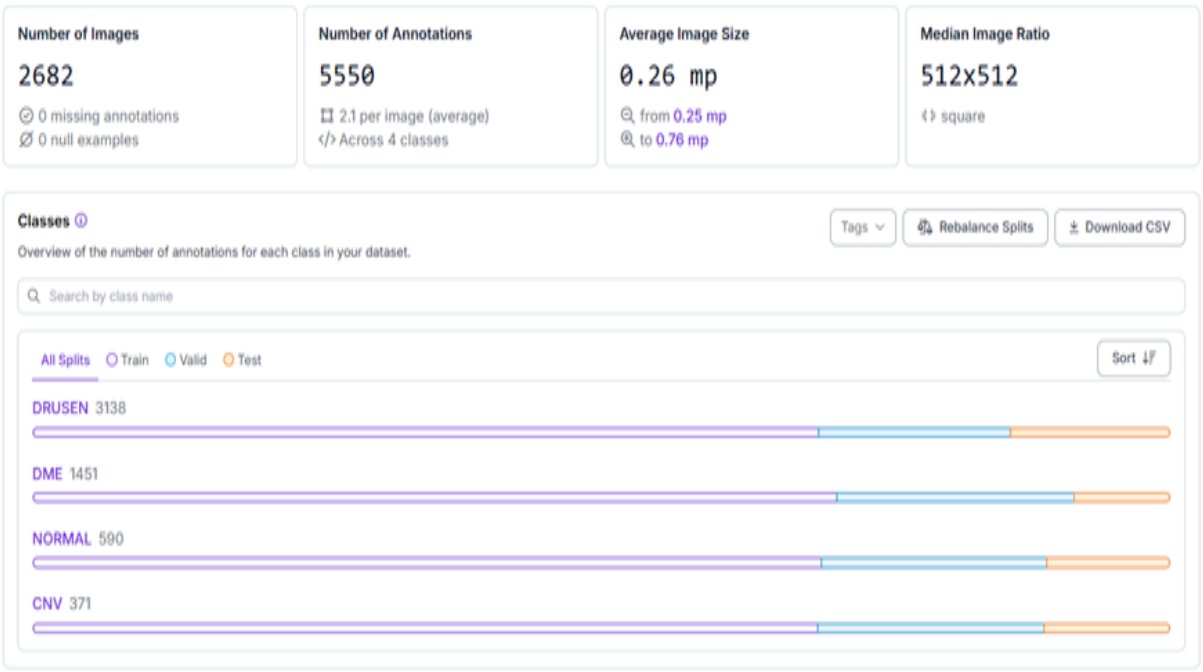
What this means:

This scan shows drusen deposits, which are a sign of early to intermediate Age-Related Macular Degeneration (AMD). This is a condition that can affect central vision as people get older.

Right now, there are no signs of advanced disease, such as bleeding, fluid, or abnormal blood vessel growth. The retina is mostly stable at this stage.

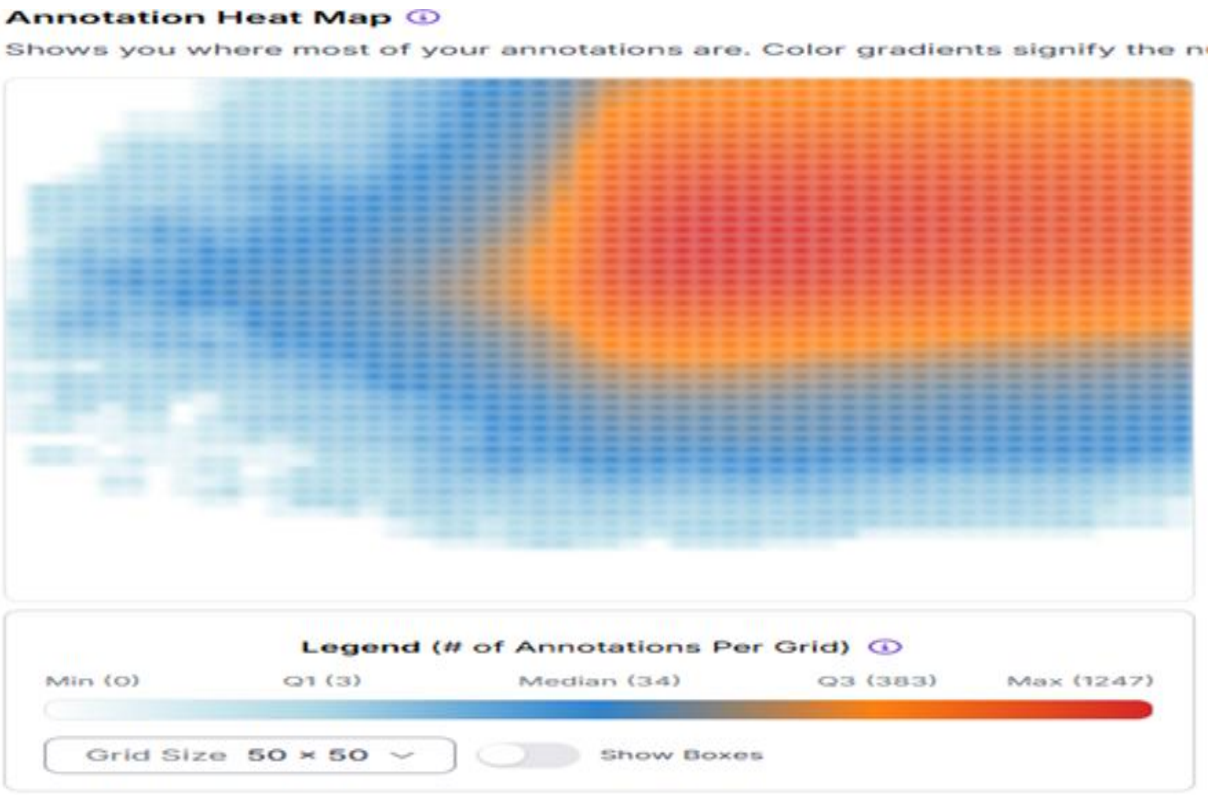
Next steps: Regular eye check-ups are important to monitor for any changes. No urgent treatment is needed at this time, but lifestyle changes (like a healthy diet and not smoking) can help slow progression.

Model Training & Dataset distribution:



[Fig 5]

Heat Map: A heatmap in the context of object detection or model performance is a visual representation of data where values are represented by colors. Here are the common types and uses of heatmaps in object detection:



[Fig 6]

Common Types of Heatmaps

1. Confidence Heatmap (Objectness Heatmap)

- What it shows: Areas of an image where the model is confident an object exists.
- How it works: Higher confidence = warmer colors (e.g., red/yellow), low confidence = cooler (blue/green).
- Use case: Helps visualize where the model "thinks" objects are, even before classification.

2. Class Probability Heatmap

- What it shows: The model's predicted probability for a specific class at each region in the image.
- Use case: Useful to diagnose false positives or class confusion.

3. Activation Heatmap (CAM/Grad-CAM)

- What it shows: Which parts of an image contributed most to a model's prediction.
- Use case: Helps interpret what part of an object the model is using to make its decision—great for model explainability.

4. Performance Heatmap (Across Classes or Locations)

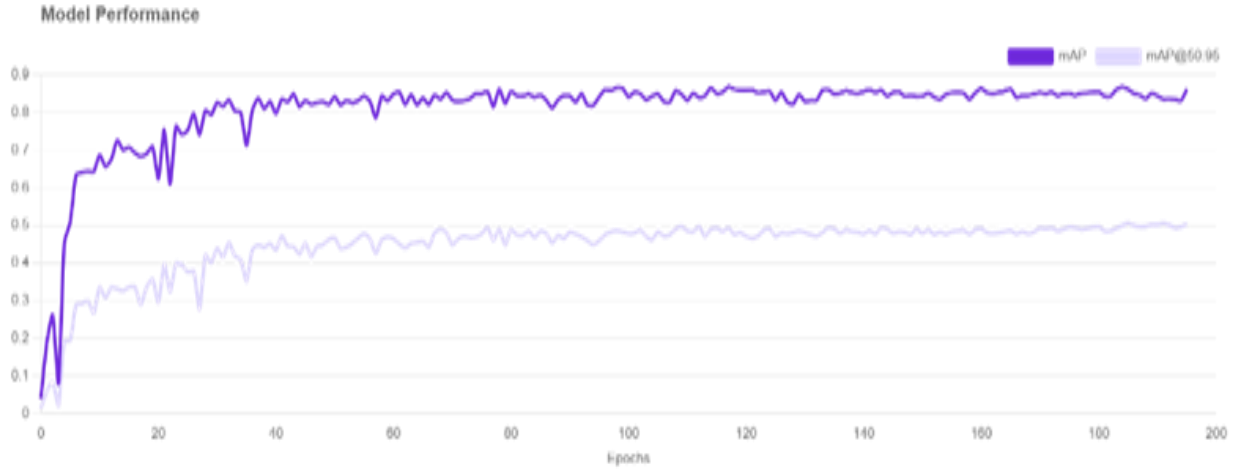
- What it shows: Errors or performance metrics (like precision, recall, or mAP) across different:
  - classes

  - image regions
  - object sizes
- Use case: Helps you spot weak spots—e.g., if the model consistently performs worse on small objects or a specific class.

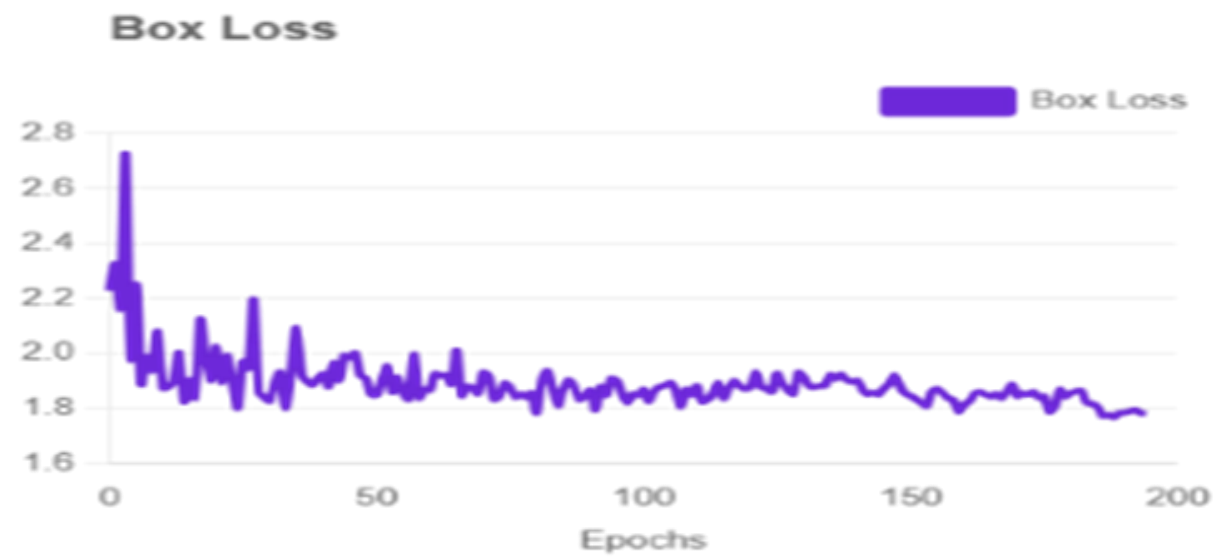
[Fig 7]

When training object detection models (like those on Roboflow), model performance is typically evaluated using mAP (mean Average Precision), which is the gold standard for detection accuracy. mAP stands for mean Average Precision and measures how well the model detects objects (localization + classification). There are two main flavors:

- mAP@0.5 – uses an IoU threshold of 0.5 (i.e., predicted box must overlap with ground truth by ≥50%)
- mAP@[.5:.95] – the COCO-style mAP, averaging over IoU thresholds from 0.5 to 0.95 in 0.05 increments (more strict, more comprehensive)

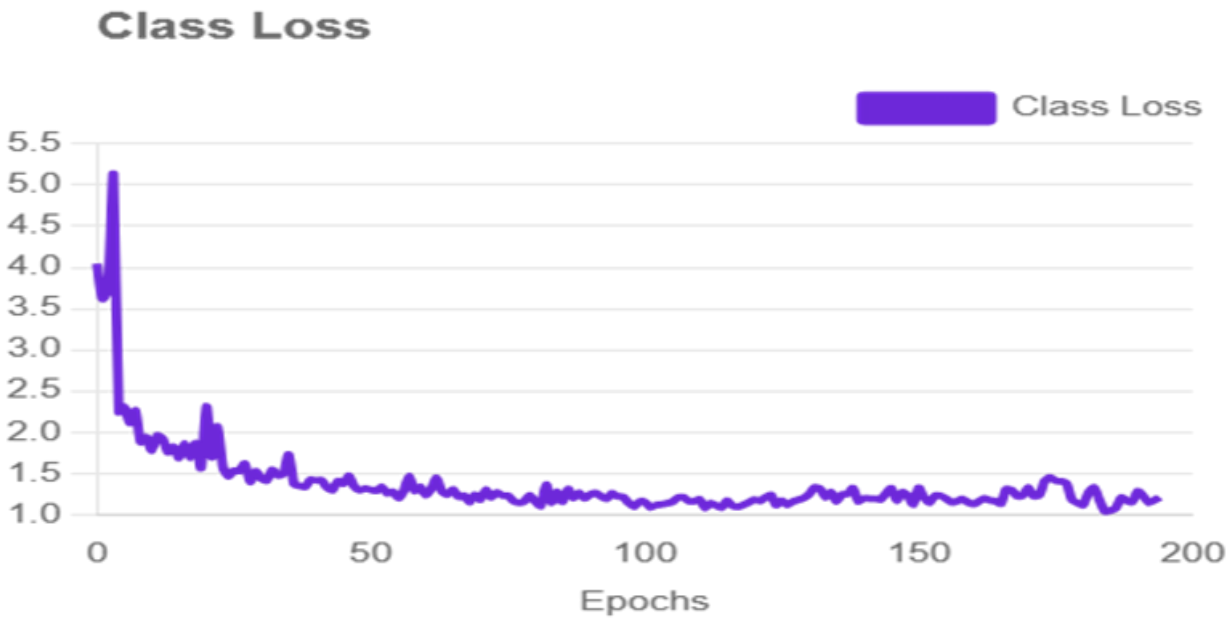


[Fig 8]



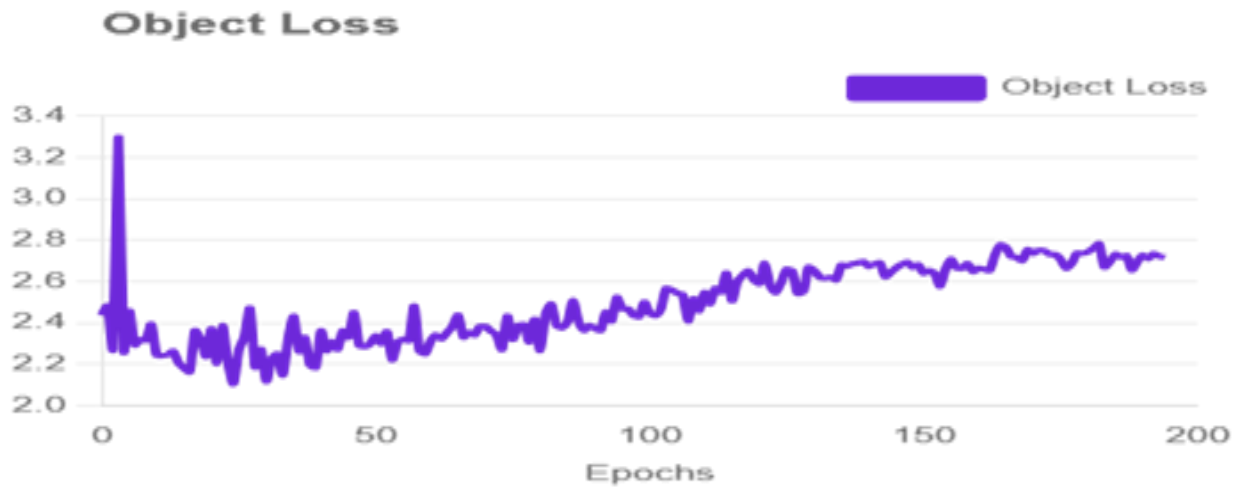
[Fig 9]

Box Loss: It measures how accurately the predicted bounding box matches the ground truth box i.e. the real object location in the image. It is used to minimize the difference in size, shape, and position between predicted and actual boxes.



[Fig 10]

Class Loss: Evaluates how well the model predicts the correct class given in your trained model for each detected object. Typically uses cross-entropy loss or binary cross-entropy. Improve the model's ability to correctly classify the detected objects.



[Fig 11]

Object Loss: Measures how confident the model is that an object exists in a particular location or anchor box. Often uses binary cross-entropy between the predicted objectness score and the actual presence/absence of an object. Ensure the model assigns high scores where objects are present and low scores where they aren't (reducing false positives and negatives)

IV. CONCLUSION

This paper offers a strong deep learning-based method for employing OCT imaging to automatically detect and report retinal illnesses like Drusen, Choroidal Neovascularization, and Diabetic Macular Edema (DME). Utilizing Convolutional Neural Networks (CNNs) and object identification models such as YOLO, the suggested system exhibits improved diagnostic precision and reliability. By eliminating subjectivity and variability in interpretations, the incorporation of a natural language generation component for converting OCT results into structured textual summaries helps standardize clinical reporting. Additionally, the technology facilitates the early identification of retinal anomalies that pose a threat to vision, allowing for prompt intervention and better patient outcomes.

This AI-assisted system helps ophthalmologists handle massive amounts of OCT scans with accuracy by drastically lowering clinician workload and improving diagnostic efficiency. Overall, our work advances the delivery of retinal care in clinical and community settings by laying the groundwork for scalable, real-time, and explainable AI tools in ocular diagnostics.

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Legends of the figures

Fig1: Image acquisition done by eye

Fig2: Proposed model of image to text formation

Fig3: Three samples output a) CNV b) DME c) DRUSEN

Fig4: Three samples output Text a) CNV b) DME c) DRUSEN

Fig 5: Distribution of data training and testing

Fig 6: Hit map of system

Fig 7: Average precision by class

Fig 8: Model performance

Fig 9: Box loss

Fig 10: Class Loss

Fig 11: Object loss