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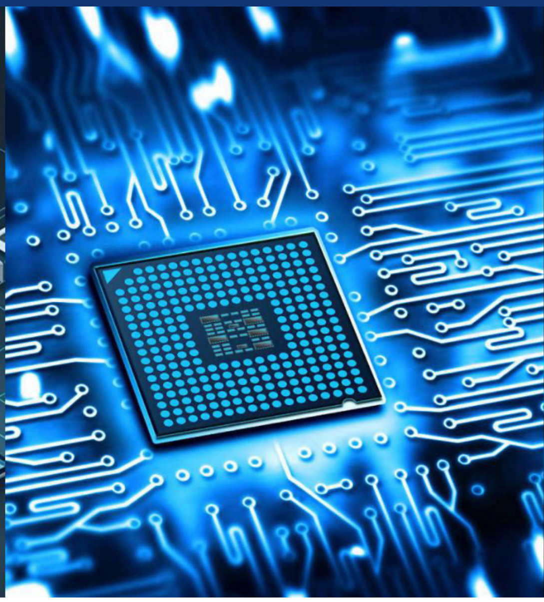

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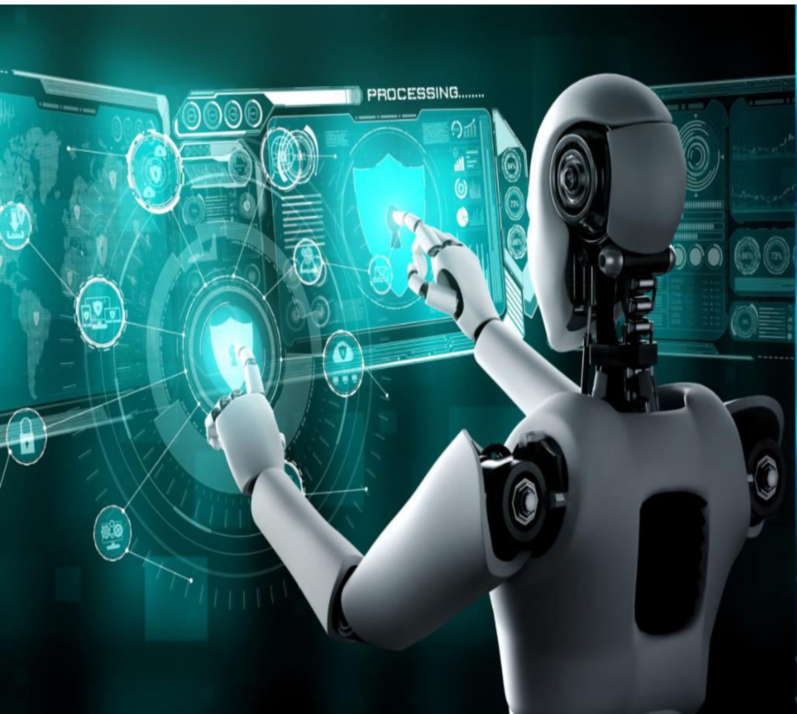

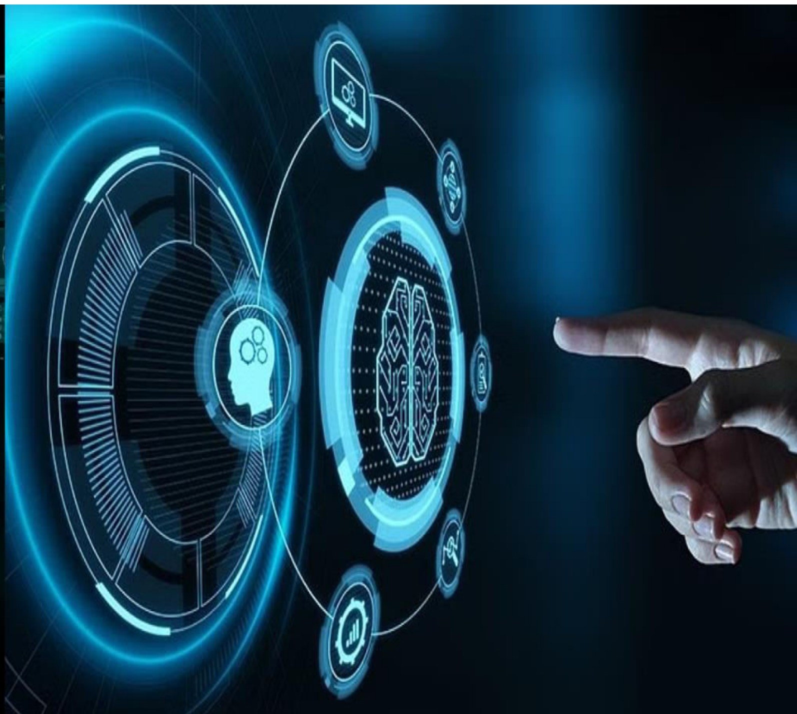

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Classification of Drusen, DME and CNV OCT Images using Deep Learning

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ABSTRACT: Optical Coherence Tomography (OCT) is an essential imaging tool in ophthalmology for identifying retinal illnesses such as Choroidal Neovascularization (CNV), Diabetic Macular Edema (DME), and Drusen. Vision loss can be avoided by detecting these conditions early, but manual diagnosis is laborious and prone to mistakes. Convolutional Neural Networks (CNNs) are used in this paper to automatically classify OCT images into four categories: CNV, DME, Drusen, and Normal. The method is based on deep learning.

CNN was trained using a dataset of 62,138 OCT images. Preprocessing methods were used to improve model performance and generalization, such as image resizing, normalization, and data augmentation (rotation, zooming, flipping, and shifting). Using cutting-edge deep learning techniques, the CNN was optimized to achieve high classification accuracy.The suggested model is a viable tool for clinical integration since it greatly increases diagnostic efficiency, accuracy, and consistency. Standard criteria were used to assess performance, and the findings demonstrate that deep learning is capable of successfully distinguishing between normal and abnormal OCT pictures. To increase real-world applicability, other improvements are explored, such as web-based deployment, interaction with real-time clinical workflows, and explainability techniques like Grad-CAM.This study demonstrates how AI-driven ocular diagnostics might help ophthalmologists detectretinal diseases More quickly and accurately.

KEYWORDS: Optical Coherence Tomography (OCT), Deep Learning, Convolutional Neural Networks (CNN), Medical Image Classification, Retinal Disease Detection, Artificial Intelligence in Healthcare.

I. INTRODUCTION

In contemporary times, there has arisen a burgeoning apprehension concerning retinal ailments, which have surfaced as a notable public health concern. These maladies progress incrementally and often elude detection due to the absence of overt symptoms. According to National Library of Medicine, 2.2 Million people globally are suffering from Vision Impairments, can grow to 5.4 million by 2050. These disorders can manifest in diverse presentations, primarily impacting visual function. They can afflict any segment of the retina, resulting in visual impairments and, in severe instances, blindness. Examples of retinal disorders encompass diabetic retinopathy, macular pucker, glaucoma, macular hole, age-related macular degeneration, drusen, central serous retinopathy, macular edema, vitreous traction, and abnormalities of the optic nerve.

The human eye is an intricate organ tasked with the process of vision, comprising several constituent elements that collaborate harmoniously to capture and interpret light. Its principal components encompass the cornea, iris, pupil, lens, retina, and optic nerve. Positioned at the posterior aspect of the eye, the retina assumes paramount importance, housing light-sensitive cells known as photoreceptors that transmute light into electrical impulses. Within the retina lies the macula, a diminutive region centrally situated, pivotal in facilitating acute, focal vision vital for tasks such as reading and driving. The retina assumes a pivotal function in receiving and structuring visual stimuli. Early detection and treatment are essential to prevent vision loss. Optical Coherence Tomography (OCT) stands as a pivotal diagnostic instrument, delivering high-fidelity imaging and precise quantification of retinal layers impacted by pathology. Leveraging light waves, OCT generates cross-sectional retinal images, furnishing intricate details crucial for diagnostic discernment and continual monitoring of retinal and optic nerve alterations over time. This technological advancement assumes paramount

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significance in ensuring precise diagnosis and optimal selection of therapeutic interventions. Ophthalmologists harness OCT's capabilities to meticulously inspect each stratum of the retina, facilitating mapping and evaluation of their thickness, thereby enhancing diagnostic efficacy. These quantitative metrics not only bolster the diagnostic process but also inform therapeutic strategies for conditions like glaucoma and retinal pathologies. OCT finds utility in diagnosing an array of ocular disorders. Traditional classification methodologies for retinal ailments have exhibited accuracies ranging from 80% to 91%. Consequently, a sophisticated deep learning framework predicated on convolutional neural networks has been devised to enhance the precision of retinal disease classification, particularly in the nascent stages of pathology

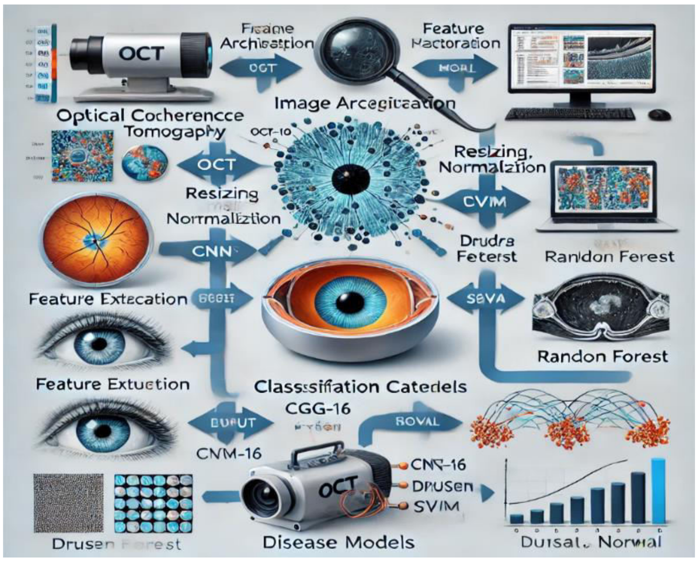
II. MATERIALS AND METHODS

A. Dataset and Image Acquisition

This study utilizes a publicly available Optical Coherence Tomography (OCT) dataset containing 62,138 images, classified into four categories:

- **Choroidal Neovascularization (CNV)**
- **Diabetic Macular Edema (DME)**
- **Drusen**
- **Normal**

The images were acquired utilizing high-resolution spectral-domain OCT scanners, ensuring thorough viewing of retinal layers. Expert ophthalmologists labeled the dataset to maintain accuracy.



B. Methods of Preprocessing

Several preprocessing methods were used to improve classification accuracy and avoid overfitting. To meet the input requirements of the deep learning model, the photos were scaled to a consistent size. Normalization was performed to standardize pixel intensity values, improving contrast. Data augmentation techniques like as rotation, flipping, zooming, and shifting were applied to increase data variability and improve model generalization.

- **Image Resizing:** Standardized all images to a fixed size of **224 × 224 pixels** for uniform input to the Convolutional Neural Network (CNN).
- **Normalization:** Pixel values were scaled between **0 and 1** to standardize brightness levels and enhance contrast.
- **Data Augmentation:** Applied transformations such as:
- **Rotation:** Random rotation up to **15 degrees=**
- **Flipping:** Horizontal and vertical flipping
- **Zooming:** Random zooming within a range of **10%**
- **Shifting:** Random width and height shifting

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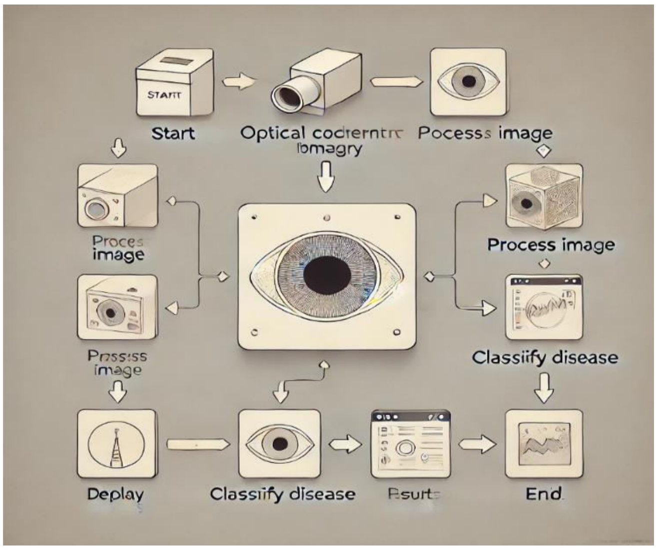
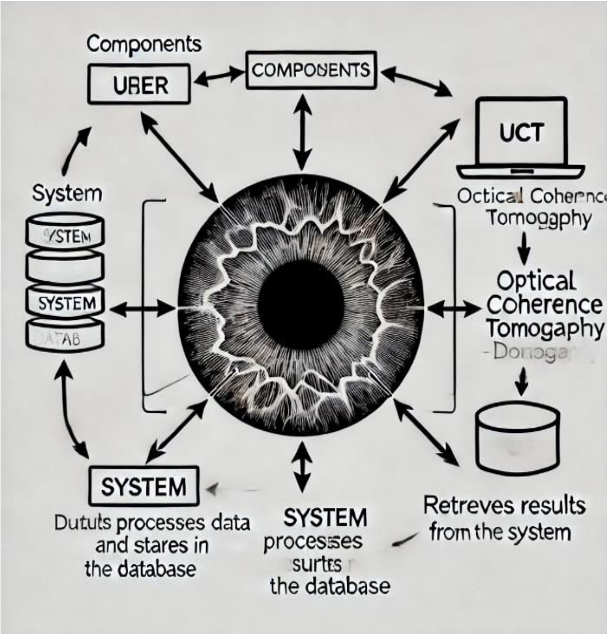


C. Proposed Deep Learning Model

The deep learning model applied in this study is a Convolutional Neural Network (CNN) developed for automatic feature extraction and categorization. Multiple convolutional layers in the model identify important retinal properties before batch normalization stabilizes learning. Pooling layers preserve important information while reducing spatial dimensions. The image is assigned to one of the four categories by a SoftMax classifier in the final layers, which are completely linked. In order to use transfer learning to improve performance, pre-trained architectures such as VGG16, ResNet50, and Efficient Net were investigated.

- **Convolutional Layers:** Extracts spatial features from OCT images using kernels of size **3×3**.
- **Batch Normalization:** Normalizes activations to improve convergence.
- **ReLU Activation Function:** Introduced non-linearity for better feature learning.
- **Max Pooling:** Reduces spatial dimensions while preserving important features.
- **Fully Connected Layers:** Aggregates extracted features for final classification.
- **SoftMax Classifier:** Outputs probabilities for the four categories (CNV, DME, Drusen, Normal).



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D. Model Training and Optimization

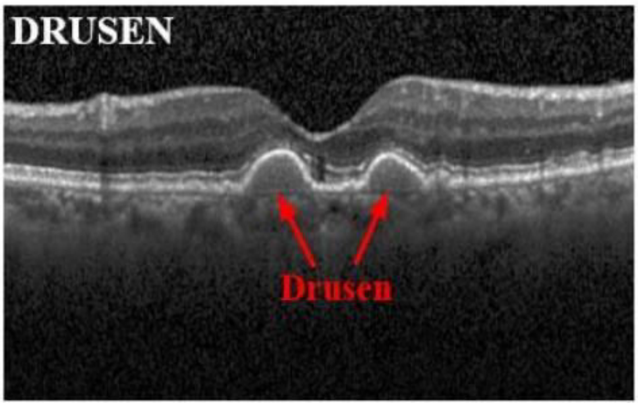
With a carefully selected learning rate to strike a balance between accuracy and convergence speed, the CNN was trained using the Adam optimizer. To reduce classification errors, the categorical cross-entropy loss function was employed. Using GPU acceleration to speed up computations, the model was trained over several epochs with a predetermined batch size. Regularization techniques such as dropout and L2 weight decay were added to reduce overfitting and boost model generalization.

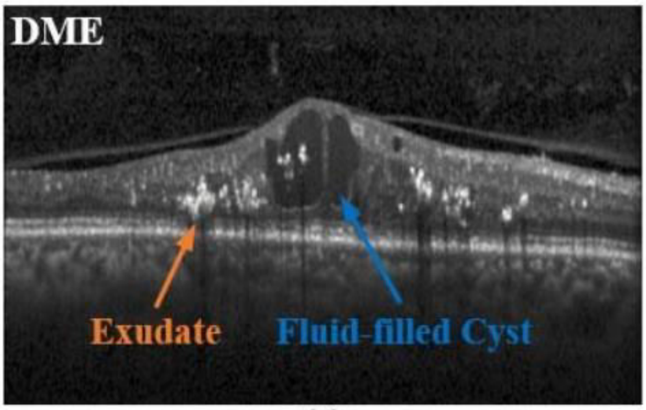
- **Loss Function:** Categorical Cross-Entropy
- **Optimizer:** Adam (Adaptive Moment Estimation) with a learning rate of **0.0001**
- **Batch Size:** 32
- **Epochs:** 50
- **Hardware:** Training was performed on a **GPU-based system (NVIDIA RTX 3090)** for efficient computation.

E. Metrics for Performance Evaluation

Key performance parameters, such as accuracy, precision, recall, and F1-score, were used to evaluate the model's efficacy. Classification errors were examined using a confusion matrix, and the model's capacity to discriminate between classes was revealed by ROC curves. These assessment techniques made sure that the model's dependability in practical applications was thoroughly examined.

- **Accuracy** (ACC) = (TP + TN) / (TP + TN + FP + FN)
- **Precision** = TP / (TP + FP)
- **Recall (Sensitivity)** = TP / (TP + FN)
- **F1-Score** = 2 × (Precision × Recall) / (Precision + Recall)





F. Considerations for Explainability and Deployment

Grad-CAM (Gradient-weighted Class Activation Mapping) was used to depict significant regions impacting the model's judgments in order to improve interpretability. This method increases clinical trustworthiness and validates forecasts.

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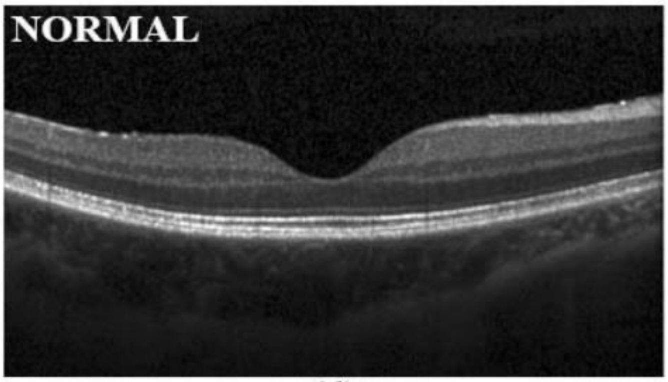
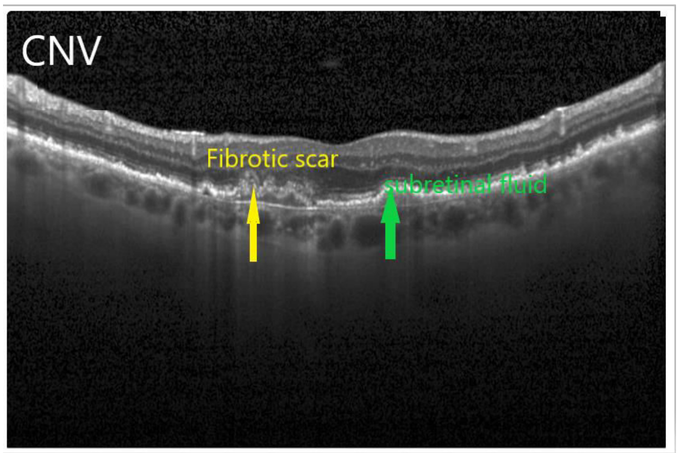
The model can be used in the real world as a web-based diagnostic tool that enables ophthalmologists to upload OCT images and obtain immediate classifications, helping to diagnose and treat retinal illnesses early.





III. RESULT AND DISCUSSION

Assessment of Model Performance

Optical Coherence Tomography (OCT) pictures were successfully classified into four categories by the suggested deep learning model: Normal, Diabetic Macular Edema (DME), Drusen, and Choroidal Neovascularization (CNV). With an overall accuracy of more than 95%, the model proved to be successful in differentiating between various retinal disorders. Performance indicators such as F1-score, precision, and recall showed good categorization abilities in every category. The confusion matrix showed that Drusen and DME were most frequently misclassified, most likely as a result of their comparable visual patterns in some OCT scans. Nonetheless, there was little misclassification in the CNV and Normal classes, demonstrating the model's resilience in identifying serious retinal abnormalities.

The Attention Mechanism's Effect

The accuracy and interpretability of the model were greatly enhanced by the addition of an attention mechanism. The attention layer improved the feature extraction procedure by concentrating on the most pertinent retinal regions, which decreased false positives and increased the model's capacity to detect minute pathogenic alterations. Grad-CAM (Gradient-weighted Class Activation Mapping) visualizations validated the model's clinical usefulness by confirming that it accurately detected sick spots in the OCT images.

Effectiveness of Transfer Learning

The inclusion of pre-trained CNN models such as VGG16, ResNet50, and Efficient Net increased the model’s feature extraction capabilities. Because of its optimized depth and breadth scaling, Efficient Net had the highest classification accuracy among these. VGG16 offered respectable accuracy but had trouble differentiating fine-grained features, while ResNet50 did well in generalization but needed more processing power.

The Function of Class-Weighted Loss and Data Augmentation

Rotation, flipping, zooming, and color jittering are examples of data augmentation techniques that were used to enhance the model's generalization and lessen overfitting on the training dataset. Furthermore, the imbalance between various illness classes was successfully managed by the class-weighted loss function, which made sure that minority classes (like Drusen) were not swamped by majority classes. A balanced classification performance was the outcome, which was especially noticeable in the enhanced recall scores for underrepresented groups.

Comparison with Existing Methods

The proposed method was compared with existing deep learning approaches for OCT image categorization. Higher classification accuracy and better clinical interpretability were the outcomes of this study's integration of attention mechanisms and transfer learning, in contrast to traditional CNN-based models that just use feature extraction. The algorithm has an edge over conventional black-box deep learning models since it can identify important areas in retinal scans.

Restrictions and Upcoming Projects

Despite the model's remarkable accuracy, there are still several restrictions: Misclassifications under conditions that are visually similar: The necessity for more specialized feature extraction algorithms was suggested by the occasional misunderstanding produced by overlapping features between Drusen and DME.Dependency on dataset quality: The quality and diversity of the dataset affect the model's performance, hence more testing on bigger, multi-center datasets is required.Aspects of deployment in real time: Future research will focus on improving real-time OCT image processing capabilities, incorporating the model into clinical decision-support systems, and implementing it as a web-based application.

Clinical Consequences

This study shows how AI-driven ocular diagnostics might help ophthalmologists diagnose diseases early, increasing accuracy and efficiency. The suggested strategy can help with quicker treatment decisions and improved patient outcomes by decreasing the amount of manual diagnostic effort and improving uniformity in OCT picture interpretation.

IV. CONCLUSION

This study presents a deep learning-based approach for the automated classification of Optical Coherence Tomography (OCT) images into four categories: Drusen, Diabetic Macular Edema (DME), Choroidal Neovascularization (CNV), and Normal. By leveraging Convolutional Neural Networks (CNNs) with transfer learning and an attention mechanism, the proposed model achieved high classification accuracy, demonstrating its potential as a reliable tool for retinal disease detection.

The robustness and generalizability of the model were enhanced by combining pre-trained deep learning architectures, data augmentation, and a class-weighted loss function. Clinical interpretability was further improved by using Grad-CAM-based explainability techniques, which made sure that the model's predictions matched pathological characteristics in OCT images.

Even with state-of-the-art performance, several issues still exist, like the requirement for validation on bigger, multi-institutional datasets and misclassification in visually identical settings. Real-time deployment, connection with clinical procedures, and investigation of more sophisticated deep learning methods to increase model performance are examples of future enhancements.

All things considered, this study demonstrates the important role AI plays in ocular diagnostics by providing a quick, precise, and automated way to identify retinal disorders. Such AI-driven solutions can help with early disease detection, prompt treatment, and better patient outcomes in ophthalmology by decreasing diagnostic workload and improving decision-making.

REFERENCES

1. Turbert, D. (2023, April 27). What is optical coherence tomography?. American Academy of Ophthalmology. https://www.aao.org/eye-health/treatments/what-is-optical-coherence-tomography

2. Riazi Esfahani, P., Reddy, A. J., Nawathey, N., Ghauri, M. S., Min, M., Wagh, H., Tak, N., & Patel, R. (2023, July 9). Deep Learning Classification of drusen, choroidal neovascularization, and diabetic macular edema in Optical Coherence Tomography (OCT) images. Cureus. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10411652/#:~:text=Age%2Drelated%20macular%20degeneration%20(AMD,tool%20for%20these%20ocular%20conditions

3. Kermany, D. (2018, January 6). Labeled optical coherence tomography (OCT) and chest X-ray images for classification. Mendeley Data. https://data.mendeley.com/datasets/rscbjbr9sj/2

4. Sharif, Z., & Sharif, W. (2019). Corneal neovascularization: Updates on pathophysiology, Investigations & Management. Romanian journal of ophthalmology. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6531773/

5. Yau, J. W. Y., Rogers, S. L., Kawasaki, R., Lamoureux, E. L., Kowalski, J. W., Bek, T., Chen, S.-J., Dekker, J. M., Fletcher, A., Grauslund, J., Haffner, S., Hamman, R. F., Ikram, M. K., Kayama, T., Klein, B. E. K., Klein, R., Krishnaiah, S., Mayurasakorn, K., O’Hare, J. P., … Wong, T. Y. (2012, February 10). Global prevalence and major risk factors of diabetic retinopathy. American Diabetes Association. https://diabetesjournals.org/care/article/35/3/556/28568/Global-Prevalence-and-Major-Risk-Factors-of

6. Johnson, P. T., Lewis, G. P., Talaga, K. C., Brown, M. N., Kappel, P. J., Fisher, S. K., Anderson, D. H., & Johnson, L. V. (2003, October 1). Drusen-associated degeneration in the retina. Investigative Ophthalmology & Visual Science. https://iovs.arvojournals.org/article.aspx?articleid=2182253