Retinal Age-related Macular Degeneration Image Classification Using Deep Learning

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***Abstract*—AMD refers to an unusual or irregular damage of the retina. In this project, we leverage deep learning techniques, specifically transfer learning with ResNet-50 to address the critical task of classifying retinal Optical Coherence Tomography (OCT) images for detection of age-related macular degeneration (AMD) and a various disease of retinal damage condition of eyes. We used a ResNet-50 CNN model that was fine-tuned to classify medical images. This model can accurately sort retinal OCT image are classify . To make results more useful for doctors we added Grad-CAM which shows a heatmap highlighting the specific areas of the retina that influenced the model decision. The project is carried out using Python, incorporating the Keras deep learning library for constructing and training neural networks, along with NumPy for performing efficient numerical computations. Google Colab is used as the development environment, offering interactive coding and access to GPU resources. In addition to achieving strong diagnostic performance the integration of Grad-CAM enhances model interpretability by visually highlighting the regions of OCT images that influence the model predictions which is essential for building trust in AI-assisted healthcare. This study demonstrates how explainable deep learning models can assist ophthalmologists in identifying and monitoring AMD at an early stage, which can result in improved outcomes for patients in actual medical environments.**

***Index Terms*—CNN, Deep Learning, Eye Disease Detection, Grad-CAM**

I. INTRODUCTION

Age-related macular degeneration is a common eye disease and it is a leading cause of vision loss among people whose age 50 or above it. A key diagnostic tool used AMD classification; However, analyzing OCT scans manually is time-consuming and prone to human error. This study intends to automate the early detection of age-related macular degeneration using deep learning using CNNs. CNNs perform really well when learning spatial hierarchies of features from image data, but training from scratch normally requires large labelled datasets. Transfer learning [5] using pre-trained models which has emerged as a strong technique. ResNet-50 a residual network structure, is used as the basic model for an OCT image classification system using fine-tuning it to discriminate healthy retinas from AMD and AMD-related disorders. Grad-CAM is used to enhance model transparencies and clinical relevance.

This research contributes to the literature on explainable artificial intelligence (XAI) in healthcare by demonstrating the integration of a high-performing CNN architecture with an ophthalmology interpretability framework.

Researchers have investigated different architectures, including VGG19[6], Inception-V3[3] and multi-scale actor networks and have achieved promising accuracy on the AMD stages. But, challenges such as interpretability and computational efficiency remain as well as accuracy of subtle retinal disease detection.

II. LITERATURE REVIEW

The use of deep learning especially convolution neural network (CNN) for classifying of OCT image of retinal eye disease. It used CNNs with transfer learning to tell normal eyes apart from AMD eyes [1]. It implemented U-Net for the pixel-wise identification of macular fluid in cases of wet AMD [2]. It uses Inception-V3[3] to correctly identify different retinal diseases, such as wet AMD. It identified early biomarkers of AMD through the application of different CNN architectures. They presented a multi-scale [5] CNN designed to capture AMD characteristics across various scales and discovered that VGG19[6] and ResNet models perform effectively in the classification of AMD. It developed a CNN framework [7] designed to identify macular atrophy in wet AMD, showing strong results. Together, these studies show the big promise of deep learning in diagnosing and tracking AMD using OCT. Detailed summarizes key studies, their methods, accuracy, dataset used in given Table 1.

Table 1: Literature review summary

Authors	Title	Database Used	Methodology	Accuracy
Lee CS, Baughman DM, Lee AY (2017) [1]	Deep learning effectively categorizes OCT scans as normal or age-related macular degeneration (OCT B-scans: normal vs AMD) using transfer learning.	OCT B-scans (normal vs AMD)	Transfer learning CNN for normal vs AMD classification	93.3 %
Schlegl T, Waldstein SM, Bogunović H, et al. (2018) [2]	Use of deep learning for automatic detection and quantification of macular fluid in OCT.	OCT images with intraretinal and subretinal fluid	U-Net for fluid segmentation in OCT.	89%
Kermany DS, Goldbaum M, Cai W, et al. (2018) [3]	Identify treatable diseases and medical diagnoses through image-based deep learning.	Large UCSD OCT dataset	Inception-V3 for multi-class OCT classification	96.6 %
Saha S, Nassisi M, Wang M, et al. (2019) [4]	Using deep learning to automatically detect and classify early signs of AMD biomarkers.	OCT images with AMD biomarkers	CNN comparison for AMD biomarker detection.	Up to 92%
Sotoudeh-Paima S, Jodeiri A, Hajizadeh F, Soltanian-Zadeh H (2022) [5]	Multi-scale CNN for Automated AMD Classification Using Retinal OCT Images: Normal, Drusen and CNV.	Retinal OCT images (normal, drusen, CNV)	Multi-scale CNN with feature fusion	94.5 %
Chen Y-M, Huang W-T, Ho W-H, Tsai J-T (2021) [6]	Using a convolutional neural network could make the process of classifyi	OCT AMD/DME datasets	Transfer learning with multiple CNN backbones.	VGG 19 ~92 %

	ng AMD easier.			
Wei W, Southern J, Zhu K, et al. (2023) [7]	In wet age-related macular degeneration optical coherence tomography.	OCT images of wet AMD with macular atrophy	CNN for macular atrophy detection in wet AMD.	95%

III. METHODOLOGY

Develop an automated multiclassification system utilizing transfer learning to detect retinal impairments in OCT images.

A. Dataset and Class Labels

The dataset used are publicly available Kermany2018 Retinal OCT dataset [3], obtained from Kaggle. The data set contains 84,495 image which are divided into four categories (Normal, Drusen, CNV, DME) shown in Fig.1

- Choroidal Neo vascularization (CNV)-Abnormal blood vessel or wet AMD which causes retina damage. This is a very critical problem of eye.
- Diabetic Macular Edema (DME) refers to swelling in the macula which indicates damage of retina which cause vision loss.
- Drusen-Yellow deposits under retina or dry AMD
- Normal- Healthy retina no disease related to eye

The data is organized into separate folders for training, validation, and testing, consistent with the Kaggle release, ensuring a balanced and standardized evaluation process.

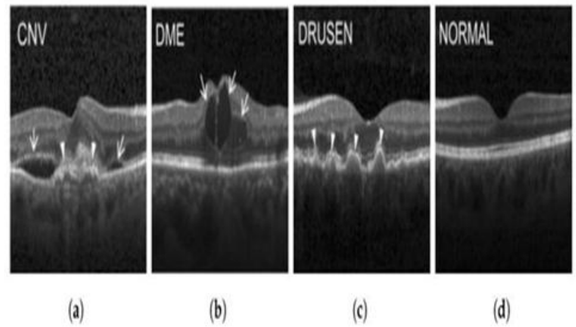

Fig. 1 Dataset from Kaggle

B. Dataset and Class Labels

Stability of data makes reliable itinerary during training and testing, that is why data have been split into three categories.

- Train Set (70%)-Using of data to train the model.
- Validation Set (10%)
- Test Set (20%)-Find metrices.

I utilized Python along with libraries such as Pandas and Scikit-learn to organize and classify data efficiently. The data was first cleaned and structured using Pandas for better handling. Subsequently, classification algorithms from Scikit-learn were applied to categorize the data into meaningful classes. This method improved the accuracy and efficiency of data classification in the study.

C. Image Resizing and Augmentation

Use ImageDataGenerator from keras for resizing and augmentation. ResNet-50 expects input images of size 224x224 pixels with three color channels. Resizing all image to this size ensures consistent input shape. Pixel values are adjusted to fit within the range of 0 to 1 or they go through a special preprocessing step designed for ResNet-50, which helps make them similar to the images used in the ImageNet dataset.

D. Model Selection

The pretrained model i.e. ResNet-50 on ImageNet the pretrained model ResNet-50 on ImageNet. Replaces top layer with the multi-class classification. Output Dense layer having 4 units. Where in SoftMax activation it multi-class classification. Build a model by using the Keras functional API with the freeze initial layer and fine-tune later layer. Layers can be frozen or unfrozen by adjusting the layer. Trainable attribute. Model use Adam optimizer and cross entropy.

E. Model Training

The model undergoes training in epochs 10, with each epoch encompassing a complete pass through the entire training dataset. Batch size was 32 which determines the number of images process prior to the adjustment of model weights. Validation data is used to assess model performance after each epoch, helping to detect overfitting. Techniques such as early stopping or learning rate (0.0001) scheduling may be implemented to enhance training efficiency. Fine-tuning consists of unfreezing certain pretrained layers and resuming training with a reduced learning rate to enhance feature extraction. Utilize model.fit() in conjunction with training and validation generators. Modify learning rates during the initial training and fine-tuning stages.

F. Grad-CAM Implementation for Model Interpretability

Grad-CAM creates a heatmap with the information that goes to the last convolutional layer for predicting the class. This will allow us to understand and ensure the model focuses on criteria that are essentially medical. The original image is used as the underlying layer and the heatmap indicates the focus of the model. To do this, we use TensorFlow's GradientTape to obtain gradient predicted a class score with respect to feature maps. Then we use these gradients to created a weighted sum of the feature maps. The heatmap is resized and normalized so that it can be plotted above the image. Final image with heatmap shows the use of OpenCV or Matplotlib tools.

IV. RESULTS AND DISCUSSION

In terms of predictive performance, the model attained an exceptionally high precision score of 0.993 (99.3%). This means that almost all images predicted to be in a disease class were correct, which means that the model was essentially preventing false positives. Having a high precision score is significant in medical imaging, because when you misidentify a healthy patient as having disease (false positive), the patient may experience unnecessary worry and engage in costly follow-up treatment due to misdiagnosis. In general, low training, validation, and test losses and precision scores that are borderline which shown in Fig.2&3 perfect indicates that the ResNet-50 architecture has strong discriminative capabilities to classify monocular retinal OCT images. The model was able to learn feature representations that were so reliable, that the potential for clinical decision-support is possible. I additionally utilized Grad-CAM which shown in Fig.4 to illustrate the areas of the OCT images that the ResNet-50 model concentrated on during its prediction process. This interpretability method validated that the model's choices were grounded in clinically significant characteristics within the retinal images, thus increasing confidence in the model's predictions and endorsing its prospective application as a dependable clinical decision-support instrument.

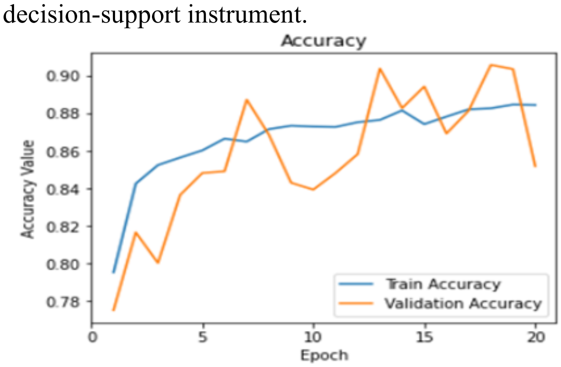

Fig. 2: Both Train and Validation accuracy steadily improve

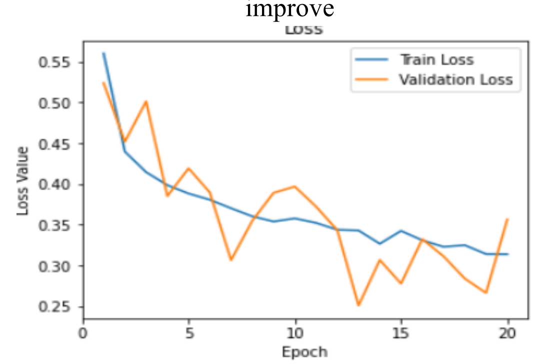

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Fig. 3: Both training and validation loss decrease over epoch

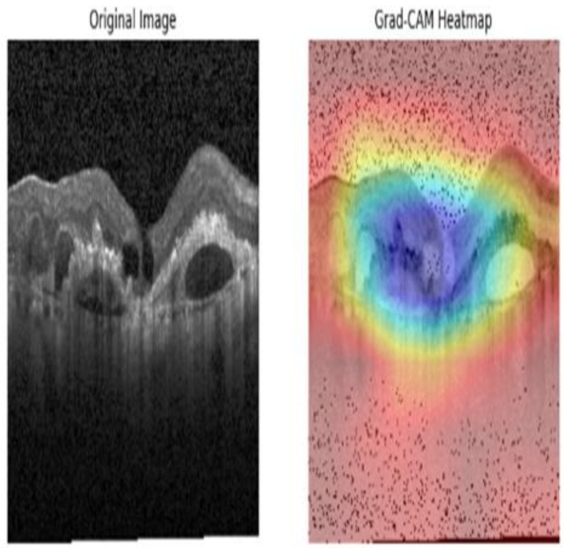

Fig.4: Result of Grad CAM

V. CONCLUSION AND FUTURE SCOPE

The study shows how well deep learning works for automatically identifying and classifying AMD from OCT images, especially when using the ResNet-50 model. Although various deep learning models have been investigated in this field, ResNet-50 has consistently demonstrated superior performance owing to its residual learning capabilities, which facilitate the extraction of complex pathological features that are often challenging to identify manually. The model achieved remarkable precision, highlighting its reliability in detecting subtle retinal abnormalities.

These results emphasize the clinical potential of frameworks based on ResNet-50 to offer swift, objective, and reproducible diagnostic assistance, thereby promoting early intervention and enhancing patient outcomes. Additionally, using explainable AI methods like Grad-CAM greatly enhances model interpretability and promotes clinical trust. In summary, this study confirms the potential of ResNet-50 in enhancing AMD diagnosis and establishes a foundation for future investigations into multi-model and multi-modal strategies in ophthalmic care.

Future studies should aim to broaden OCT datasets to include a wider range of age demographics and disease variations, thus minimizing bias and improving the generalizability of models. Enhancing model interpretability through explainable AI methods such as Grad-CAM, saliency maps, and attention mechanisms is crucial for fostering clinician and regulatory confidence in AI-assisted decision-support systems. Moreover, the integration of multimodal data comprising fundus images, patient histories, and genetic data could further enhance diagnostic precision and clinical significance.

REFERENCES

[1] C. S. Lee, D. M. Baughman, and A. Y. Lee, “Deep learning is effective for classifying normal versus age-related macular degeneration OCT images,” *Ophthalmology Retina*, vol. 1, no. 4, pp. 322–327, 2017.

[2] T. Schlegl, S. M. Waldstein, H. Bogunovic, F. Endstraßer, A. Sadeghipour, A. M. Philip, and U. Schmidt-Erfurth, “Fully automated detection and quantification of macular fluid in OCT using deep learning,” *Ophthalmology*, vol. 125, no. 4, pp. 549–558, 2018.

[3] D. S. Kermany, M. Goldbaum, W. Cai, C. C. Valentim, H. Liang, S. L. Baxter, and K. Zhang, “Identifying medical diagnoses and treatable diseases by image-based deep learning,” *Cell*, vol. 172, no. 5, pp. 1122–1131, 2018.

[4] S. Saha, M. Nassisi, M. Wang, S. Lindenberg, Y. Kanagasingam, S. Sadda, and Z. J. Hu, “Automated detection and classification of early AMD biomarkers using deep learning,” *Scientific Reports*, vol. 9, no. 1, p. 10990, 2019.

[5] S. Sotoudeh-Paima, A. Jodeiri, F. Hajizadeh, and H. Soltanian-Zadeh, “Multi-scale convolutional neural network for automated AMD classification using retinal OCT images,” *Computers in Biology and Medicine*, vol. 144, p. 105368, 2022.Y. M. Chen, W.

[6] T. Huang, W. H. Ho, and J. T. Tsai, “Classification of age-related macular degeneration using convolutional-neural-network-based transfer learning,” *BMC Bioinformatics*, vol. 22, suppl. 5, p. 99, 2021.

[7] W. Wei, J. Southern, K. Zhu, Y. Li, M. F. Cordeiro, and K. Veselkov, “Deep learning to detect macular atrophy in wet age-related macular degeneration using optical coherence tomography,” *Scientific Reports*, vol. 13, no. 1, p. 8296, 2023.