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RETINOMINDNET: AUTOMATED NEURODEGENERATIVE RISK PROFILING THROUGH OCT RETINAL PATTERN LEARNING

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Abstract: Neurodegenerative diseases such as Alzheimer’s disease, Parkinson’s disease, and multiple sclerosis are progressive disorders that cause irreversible neuronal damage and often remain undetected until advanced stages. Early identification of disease-associated biomarkers is therefore essential for timely intervention and improved patient outcomes. This study presents RetinoMindNet, an automated deep learning framework for neurodegenerative risk profiling using Optical Coherence Tomography (OCT) retinal images. The retina serves as a non-invasive indicator of neurological health because of its close structural and developmental relationship with the central nervous system. The proposed approach employs a transfer learning-based VGG19 convolutional neural network to extract discriminative retinal features and classify retinal abnormalities associated with neurodegenerative risk. Image preprocessing techniques, including resizing, normalization, and augmentation, are applied to enhance data quality and model generalization. The system is trained and evaluated on a publicly available OCT dataset containing multiple retinal disease categories and healthy samples. Experimental results demonstrate high classification accuracy, precision, recall, and F1-score, highlighting the effectiveness of deep learning-driven retinal analysis for scalable, accessible, and efficient neurodegenerative risk assessment.

Index Terms – Neurodegenerative Diseases, Optical Coherence Tomography (OCT), Retinal Imaging, Deep Learning, VGG19, Transfer Learning, RetinoMindNet, Disease Classification, Medical Image Analysis, Early Detection.

I. INTRODUCTION

Recent advancements in artificial intelligence, medical imaging, and computational analysis have significantly improved the ability to detect diseases at earlier stages and support clinical decision-making. The combination of deep learning algorithms with high-resolution imaging technologies has enabled automated extraction of meaningful patterns from complex biomedical data. Among various imaging modalities, Optical Coherence Tomography (OCT) has emerged as a valuable non-invasive technique that provides detailed cross-sectional visualization of retinal structures. Since the retina shares anatomical and developmental characteristics with the central nervous system, retinal abnormalities can serve as important indicators of neurological health and disease progression.Neurodegenerative diseases, including Alzheimer’s disease, Parkinson’s disease, and multiple sclerosis, are chronic disorders characterized by the gradual loss of neuronal structure and function. These conditions often remain undetected during their early stages because clinical symptoms typically appear only after substantial neuronal damage has occurred. Consequently, early diagnosis remains a major challenge in healthcare. Conventional diagnostic methods such as magnetic resonance imaging, positron emission tomography, and cerebrospinal fluid analysis are often costly, invasive, and difficult to implement for large-scale screening programs. Therefore, there is a growing demand for accessible, efficient, and non-invasive approaches capable of identifying disease-related biomarkers before the onset of severe symptoms.Retinal imaging has gained increasing attention as a promising tool for neurological assessment because structural changes within retinal layers frequently reflect pathological alterations occurring in the brain. Advances in deep learning have further strengthened the capability of retinal image analysis by enabling automatic feature extraction and recognition of subtle disease-related patterns. Convolutional Neural Networks (CNNs), particularly transfer learning-based architectures, have demonstrated remarkable success in medical image classification tasks due to their ability to learn complex visual representations from large datasets.This study presents RetinoMindNet, an automated neurodegenerative risk profiling framework based on OCT retinal pattern learning. The framework employs a pre-trained VGG19 deep learning architecture to analyze retinal OCT images and identify abnormalities associated with neurodegenerative risk. Through image preprocessing, feature extraction, and multi-class classification, the framework achieves reliable prediction performance. The integration of retinal imaging and artificial intelligence provides a scalable and efficient approach for early screening, assisting healthcare professionals in identifying individuals at potential risk of neurodegenerative disorders while supporting improved clinical decision-making and patient care outcomes worldwide.

II. Related Works

Article[1] "Retinal Disease Classification from OCT Images Using Deep Learning Algorithms" by Jongwoo Kim and Loc Tran in 2021: This study investigated the effectiveness of deep learning techniques for retinal OCT image classification. Multiple convolutional neural network architectures were evaluated for identifying retinal abnormalities from OCT scans. Transfer learning was applied to improve performance on limited medical datasets. The research compared binary and multi-class classification strategies. Experimental results demonstrated significant improvements in diagnostic accuracy. The study highlighted the importance of automated retinal image analysis in reducing clinician workload. Findings indicated that deep learning models can serve as reliable tools for ophthalmic disease screening and diagnosis.

Article[2] "Deep Learning-Based Methods for Alzheimer's Diagnosis Using Retinal OCTA: A Review" by Xiaoyue Shan, Jiping Xiong, Shuxin Wang, Qingyuan Peng, Ling Chen, and Xiaoyan Ying in 2023: This review examined the application of deep learning models in Alzheimer's disease detection using retinal OCT and OCTA images. Various neural network architectures and retinal biomarkers were analyzed. The study discussed vascular and structural retinal alterations associated with cognitive decline. Challenges related to dataset availability and model generalization were identified. The review emphasized the importance of explainable artificial intelligence in healthcare. Future directions included multimodal data fusion and longitudinal analysis. The findings supported the use of retinal imaging as a non-invasive neurological assessment tool.

Article[3] "Interpretable Vision Transformer for Diagnosing Macular Diseases Using Optical Coherence Tomography" by J.Z. He, J.X. Wang, Z.Y. Han, J. Ma, C.J. Wang, and M. Qi in 2023: This research proposed an interpretable Vision Transformer framework for OCT image classification. Attention mechanisms were utilized to identify disease-relevant retinal regions. The model achieved competitive classification performance compared to conventional CNN approaches. Visualization techniques enhanced transparency and clinical trust. The study demonstrated the capability of transformer architectures in medical imaging tasks. Experimental evaluations confirmed robustness across different retinal disease categories. The work highlighted the importance of explainable diagnostics in clinical environments.

Article[4] "Enhanced Deep Learning Model for Classification of Retinal Optical Coherence Tomography Scans" by Olanrewaju Kehinde Oguntade, Stephen Aikins, Carmen Poon, and Yanhui Hu in 2023: This study introduced an enhanced deep learning framework for OCT image classification. Modified ResNet architecture and optimization strategies were employed to improve convergence. Extensive preprocessing and augmentation techniques were applied. The proposed model achieved superior classification accuracy compared with baseline methods. Cross-validation experiments confirmed model reliability. The research emphasized balanced performance across disease categories. Results demonstrated the suitability of advanced deep learning techniques for computer-aided retinal diagnosis.

Article[5] "Deep Learning and Machine Learning Algorithms for Retinal Image Analysis in Neurodegenerative Disease: Systematic Review of Datasets and Models" by T. Bahr, T.A. Vu, J.J. Tuttle, and colleagues in 2024: This systematic review analyzed machine learning and deep learning approaches for retinal image analysis in neurodegenerative diseases. Various datasets, imaging modalities, and neural network models were examined. The study identified trends in retinal biomarker detection. Challenges involving dataset heterogeneity and model reproducibility were discussed. Comparative evaluation of algorithms highlighted strengths and limitations. Recommendations for future research were provided. The review established retinal imaging as an important area for neurological disease assessment.

Article[6] "Eye-AD: A Generative AI Framework for Alzheimer's Disease Prediction" by Changhee Han, Sofiane Clabaut, Ziftu Gurmessa, Thibault Napolitano, Elias Boutros, Gabriel Kreiman, Marinka Žitnik, Sylvia Plevritis, Akshay Chaudhari, and Daniel Rubin in 2024: This research presented a generative artificial intelligence framework for predicting Alzheimer's disease using retinal imaging data. Self-supervised learning techniques enhanced feature representation quality. The framework integrated imaging biomarkers with clinical information. Cross-cohort evaluation demonstrated promising generalization capabilities. Bias assessment and model reliability were carefully examined. Results indicated strong potential for early disease screening. The study contributed to trustworthy and scalable AI-assisted diagnosis.

Article[7] "Evaluating Deep Learning Models for Classifying OCT Images with Limited Data and Noisy Labels" by Aleksandar Miladinović, Alessandro Biscontin, Miloš Ajčević, Simone Kresevic, Agostino Accardo, Dario Marangoni, Daniele Tognetto, and Leandro Inferrera in 2024: This study evaluated the impact of limited datasets and noisy labels on OCT image classification. Multiple deep learning architectures were compared under different conditions. The analysis quantified performance degradation caused by annotation errors. Experimental findings showed that larger datasets improved robustness. The research provided practical recommendations for medical dataset preparation. Strategies for quality assurance and annotation management were discussed. Results supported the development of reliable clinical AI systems.

Article[8] "Deep Learning-Based Classification of Eye Diseases Using OCT Images" by Mohamed Elkholy and co-authors in 2024: This work applied convolutional neural networks for automated classification of retinal diseases from OCT images. Feature extraction was performed using deep learning techniques. The model successfully differentiated normal and diseased retinal conditions. Data augmentation enhanced classification performance. Comparative analysis showed improved accuracy relative to conventional methods. The framework demonstrated effectiveness in early disease identification. The research reinforced the importance of AI-based ophthalmic screening systems.

Article[9] "Stitched Vision Transformer for Age-Related Macular Degeneration Detection Using Retinal OCT Images" by Mohammad Mahdi Azizi, Setareh Abhari, and Hedieh Sajedi in 2024: This study introduced a stitched Vision Transformer architecture for AMD detection from OCT scans. Multiple pretrained transformer modules were integrated into a unified framework. The model achieved high classification accuracy while maintaining computational efficiency. Transfer learning reduced training requirements. Experiments demonstrated strong performance on clinical datasets. The research highlighted the advantages of transformer-based approaches in retinal imaging. Findings supported rapid deployment of AI diagnostic systems.

Article[10] "Automated Binary Classification of OCT Images for Diabetic Retinopathy Detection Using Transformers" by Harold Weld in 2024: This study explored transformer-based architectures for diabetic retinopathy detection using OCT images. Patch embedding and self-attention mechanisms were adapted for retinal image analysis. Experimental results showed competitive performance compared with CNN models. The framework demonstrated effective feature learning from limited data. Regularization techniques improved model stability. Open-source implementation enhanced reproducibility. The study validated transformer networks for ophthalmic disease classification.

Article[11] "AI-Assisted Ophthalmic Imaging for Early Detection of Neurodegenerative Diseases" by Hajar Nasir Tukur, Olivier Uwishema, Hatice Akbay, Dalal Sheikhah, and Inês Filipa Silva Correia in 2025: This review investigated the role of artificial intelligence in ophthalmic imaging for neurodegenerative disease detection. Retinal biomarkers associated with Alzheimer's and Parkinson's diseases were analyzed. AI models demonstrated strong diagnostic performance across multiple studies. The review discussed sensitivity, specificity, and clinical applicability. Ethical considerations and model interpretability were examined. Challenges related to dataset bias were highlighted. Findings supported the integration of AI-assisted retinal screening into healthcare practice.

Article[12] "Alzheimer's Disease Classification Using Retinal OCT: TransNetOCT and Swin Transformer Models" by Siva Manohar Reddy Kesu, Neelam Sinha, Hariharan Ramasangu, and Thomas Gregor Issac in 2025: This study developed advanced deep learning models for Alzheimer's disease classification using retinal OCT images. Both TransNetOCT and Swin Transformer architectures were evaluated. Extensive preprocessing and feature extraction techniques were employed. The proposed models achieved high classification accuracy for distinguishing Alzheimer's patients from healthy controls. Explainability methods identified important retinal regions contributing to predictions.

III. Problem Stetement

Neurodegenerative diseases such as Alzheimer's disease, Parkinson's disease, and multiple sclerosis progress gradually and often remain undiagnosed until significant neuronal damage has already occurred. Existing diagnostic techniques, including MRI, PET imaging, and cerebrospinal fluid analysis, are expensive, time-consuming, invasive, and not suitable for large-scale early screening. Although retinal OCT imaging provides valuable insights into neurological health, manual interpretation of retinal scans is challenging, labor-intensive, and subject to inter-observer variability. Furthermore, subtle retinal changes associated with neurodegeneration are difficult to identify through conventional examination methods. Therefore, there is a critical need for an accurate, automated, non-invasive, and scalable approach capable of detecting retinal biomarkers linked to neurodegenerative risk at an early stage.

IV. Objectives

The primary objective of this study is to develop an efficient and reliable system for early neurodegenerative risk assessment through retinal OCT image analysis. The study aims to identify retinal abnormalities that may serve as potential biomarkers of neurological disorders using advanced deep learning techniques. Another objective is to automate the classification process, reducing dependence on manual interpretation and improving diagnostic consistency. The study also focuses on enhancing prediction accuracy through effective image preprocessing and feature extraction methods. Additionally, it seeks to provide a scalable, non-invasive, and cost-effective screening approach that supports healthcare professionals in early detection, clinical decision-making, and timely intervention for neurodegenerative diseases.

V. Methodology

1)Data Collection: dataset used in this study was obtained from a publicly available Kaggle repository containing Optical Coherence Tomography (OCT) retinal images. The dataset consists of multiple retinal disease categories, including Age-related Macular Degeneration, Diabetic Retinopathy, Choroidal Neovascularization, Central Serous Retinopathy, Macular Hole, Diabetic Macular Edema, and healthy retinal samples. These retinal images provide valuable information regarding structural abnormalities that may be associated with neurodegenerative disorders and serve as the foundation for model development.

2)Data Preprocessing: OCT images were resized to a uniform resolution of 224×224 pixels to meet the input requirements of the VGG19 architecture. Image normalization was applied to scale pixel values and improve training efficiency. In addition, data augmentation techniques such as rotation, flipping, shifting, and zooming were utilized to increase dataset diversity, enhance model generalization, and reduce the risk of overfitting.

3)Feature Extraction: extraction was performed using the pre-trained VGG19 convolutional neural network model. The convolutional layers automatically extracted important retinal features, including textures, edges, and structural patterns from OCT images. These deep features captured disease-related information and provided meaningful representations for accurate classification of retinal abnormalities associated with neurodegenerative risk.

4)Model Selection: was selected as the primary deep learning model because of its proven effectiveness in medical image classification applications. The architecture contains multiple convolutional layers capable of learning hierarchical image features with high precision. Transfer learning was employed to utilize previously learned knowledge from the ImageNet dataset and adapt it to retinal OCT image analysis.

5)Model Training: selected VGG19 model was trained using the processed OCT dataset with categorical cross-entropy as the loss function and the Adam optimizer for weight optimization. The dataset was divided into training, validation, and testing subsets to ensure reliable performance evaluation. Early stopping and model checkpoint techniques were implemented to prevent overfitting and preserve the best-performing model.

6)Model Evaluation: trained model was evaluated using various performance metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. These evaluation measures provided a comprehensive assessment of classification performance across all retinal disease categories. The results demonstrated the model's capability to accurately identify retinal abnormalities and healthy conditions.

7)Integration with Flask: final trained VGG19 model was integrated into a Flask-based web application to provide a simple and interactive user interface. The application allows users to upload OCT retinal images and receive automated predictions in real time. This integration enhances accessibility, usability, and practical deployment for neurodegenerative risk screening and retinal disease classification.

VI. SYSTEM ARCHITECTURE

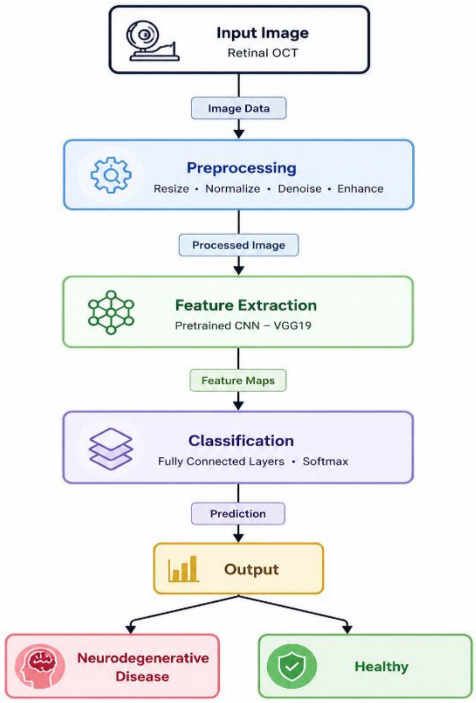

Fig 1: System Architecture for Automated Neurodegenerative Risk Classification Using OCT Retinal Images

The system architecture illustrates the complete workflow for automated neurodegenerative risk classification using retinal Optical Coherence Tomography (OCT) images. The process begins with the acquisition of a retinal OCT image, which serves as the input to the framework. The image then undergoes preprocessing operations including resizing, normalization, denoising, and enhancement to improve image quality and ensure consistency for model analysis. The processed image is forwarded to the feature extraction stage, where a pre-trained VGG19 convolutional neural network automatically learns important retinal structures, textures, and disease-related patterns. The extracted feature maps are subsequently passed to the classification module consisting of fully connected layers and a Softmax activation function. This stage performs predictive analysis by assigning the image to the most appropriate class based on learned features. Finally, the system generates an output indicating whether the retinal image corresponds to a healthy condition or exhibits characteristics associated with neurodegenerative disease risk, enabling accurate and efficient screening support.

VII. Experimental Results

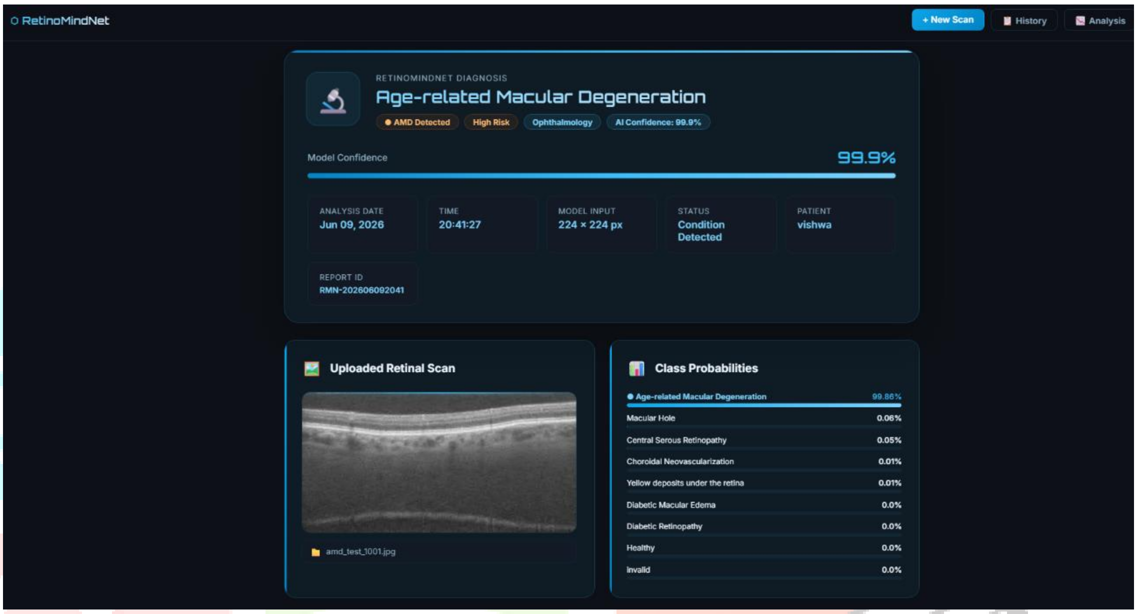

Fig. 2: RetinoMindNet Web Interface for Automated OCT Retinal Image Classification and Disease Prediction

The figure illustrates the Flask-based web application interface used for retinal OCT image analysis and disease classification. It displays the uploaded retinal scan, prediction confidence score, detected retinal condition, and class-wise probability distribution generated by the VGG19 deep learning model for clinical decision support.

Fig. 2: Scan History Dashboard for Retinal Disease Analysis and Prediction Monitoring

The figure presents the scan history dashboard of the RetinoMindNet web application, displaying previously analyzed retinal OCT scans along with summary statistics, disease distribution, and condition frequency charts. It enables users to track historical predictions, monitor classification trends, filter records based on multiple criteria, and visualize the occurrence of different retinal conditions for effective analysis and decision support.

VIII. CONCLUSION AND FUTURE WORKS

In this research, an automated framework for neurodegenerative risk profiling using retinal Optical Coherence Tomography images was developed and evaluated through a deep learning approach based on the VGG19 architecture. The study demonstrated that retinal imaging can serve as a valuable non-invasive source of biomarkers for identifying disease-related abnormalities associated with neurological disorders. Image preprocessing, transfer learning, feature extraction, and multi-class classification techniques contributed to reliable predictive performance across different retinal conditions. Experimental results indicated high classification accuracy and effective discrimination between healthy and abnormal retinal patterns, highlighting the potential of artificial intelligence in supporting early screening and clinical assessment. The developed Flask-based application further improved accessibility by providing real-time image analysis and automated prediction capabilities. Future work may focus on integrating larger and more diverse datasets collected from multiple clinical centers to improve generalization and robustness. Additional enhancements may include multimodal data fusion with OCTA, MRI, or clinical records, transformer-based architectures for improved feature learning, and explainable artificial intelligence techniques to increase transparency. Longitudinal studies, cloud-based deployment, real-time monitoring systems, and extensive clinical validation can further strengthen reliability and support practical adoption in healthcare environments for earlier detection, better risk stratification, improved patient management, enhanced diagnostic confidence, and outcomes.

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