Identification of Memory Loss disease by Ocular Biomarkers using Deep Learning Models

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***Abstract*—This study investigates the use of deep learning techniques to analyze retinal images captured through Optical Coherence Tomography Angiography (OCTA) for the detection of Alzheimer's disease (AD). By assessing changes in retinal blood vessel properties, such as flow and density, the method identifies patterns linked to AD. The research expands on existing approaches and integrates clinical insights to create a non- invasive, cost-effective tool for early diagnosis. It also emphasizes the importance of specific regions of the retina in the detection process, offering valuable information for medical professionals and advancing the understanding of retinal biomarkers as- sociated with AD. The results highlight the potential of this approach to improve the accuracy and accessibility of diagnosing neurodegenerative diseases.**

***Index Terms*—OCTA, Alzheimer's Disease, Polar Transformation**

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurological condition that causes cognitive and functional decline, impacting millions worldwide. Early diagnosis is crucial for effective treatment and improving patient outcomes. However, conventional diagnostic tools such as MRI and PET scans, while accurate, are costly, time-consuming, and often inaccessible in underserved areas. These challenges underscore the need for affordable and non-invasive alternatives.

Recent studies have revealed strong links between ocular and brain health, particularly noting a decrease in blood vessel density within specific retinal layers such as the superficial parafoveal and choriocapillaris in individuals with AD. These findings have increased interest in Optical Coherence Tomography Angiography (OCTA), a high-resolution imaging technique that captures detailed views of the retinal microvasculature, including the superficial vascular complex (SVC), deep vascular complex (DVC), and choriocapillaris (CC).

Clinical evaluation tools like the Early Treatment Diabetic Retinopathy Study (ETDRS) grid allow for localized analysis by dividing the retina into distinct zones to assess vascular features. Research has shown that patients with AD exhibit

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notable reductions in metrics such as vascular area density and vascular length density in regions like the nasal-outer, superior-inner, and inferior-inner sections.

While deep learning has shown promise in medical image analysis for AD detection, many current models lack integration of region-specific clinical knowledge. This limits their ability to produce results that align with clinical interpretations or offer transparent, interpretable insights.

To address this, the current study proposes a novel deep learning approach that incorporates clinical region-based analysis of OCTA images for AD detection. By converting OCTA images from a Cartesian to a radial coordinate system, the model mimics sector-based clinical evaluations, allowing for targeted feature extraction. A weighted matrix is also used during training to prioritize clinically significant regions, ensuring alignment with medical observations. Explainability techniques further confirm the model's consistency with clinical patterns, reinforcing its ability to identify meaningful associations between retinal biomarkers and AD.

This innovative method offers a promising advancement in early AD diagnosis, combining the strengths of deep learning with clinical expertise to deliver an efficient, interpretable, and non-invasive diagnostic tool.

II. RESEARCH OBJECTIVES

- Develop a Precise and Fast Detection System for Alzheimer's Disease (AD) Using CNN Architecture: The primary goal is to build a reliable Convolutional Neural Network (CNN)-based model capable of analyzing OCTA images to detect biomarkers associated with Alzheimer's disease with high accuracy and efficiency. By harnessing deep learning, this approach aims to provide a scalable, affordable alternative to traditional diagnostic methods, promoting early and accessible diagnosis in clinical environments.
- Enhance Diagnostic Methods by Automating with Deep Learning: Existing diagnostic procedures often depend on manual interpretation and invasive techniques, which are not only time-intensive and costly but also susceptible to human error. Incorporating deep learning allows for the automation of these processes, reducing subjectivity, increasing reliability, and minimizing the time and re- sources needed—making real-time clinical implementation feasible.
- Extract Disease-Specific Features from OCTA Image Data: Alzheimer's disease manifests through particular retinal abnormalities, including decreased vascular area and length densities, observable in OCTA scans. The system aims to accurately identify and analyze these subtle indicators using sophisticated image processing methods, facilitating early-stage detection of AD.
- Evaluate System Performance Through Comparison with Existing Diagnostic Techniques: The effectiveness of the proposed model will be assessed by comparing its performance to conventional diagnostic tools and leading- edge methods, focusing on accuracy, speed, and interpretability. This comparative evaluation will help confirm the model's clinical relevance and its potential to enhance current practices in AD diagnosis.

III. LITERATURE SURVEY

[1] This paper presents a deep-learning model called Polar-Net for detecting Alzheimer's Disease using Optical Coherence Tomography Angiography (OCTA) images. This model aims to enhance interpretability and clinical relevance with region-based analysis, utilizing a dataset of 199 OCTA images from 114 AD patients and 566 images from 291 healthy subjects, with additional validation from the OCTA- 500 dataset. However, it notes the minimal improvement from prior knowledge matrices and the potential issue with high- dimensional features.

[2] Which focuses on developing a machine learning model for early diagnosis of Alzheimer's Disease. It employs an ensemble-based approach using classifiers such as Gaussian NB, Decision Tree, Random Forest, XG Boost, and Voting Classifier. The researchers utilized the OASIS dataset, which includes MRI data from 150 individuals aged 60-96, with 64 subjects diagnosed with dementia and 72 non-demented. The study highlights the importance of data preprocessing, including feature selection, outlier detection, and data augmentation, to improve model performance. Despite the promising results, the paper notes the need for further optimization in removing redundant features and extracting more relevant ones to enhance the model's accuracy.

[3] explores the use of deep learning methods for diagnosing Alzheimer's disease (AD). It delves into the application of AD-related biomarkers, feature extraction techniques, and evaluates the performance of deep learning models in detecting AD from medical images. The study utilizes several publicly available datasets commonly used in AD detection research, such as ADNI, OASIS, and AIBL. However, the study acknowledges challenges such as a lack of sufficient data samples, which can hinder generalization, and the time- consuming manual annotation

[4] aims to distinguish between AD patients and healthy subjects by analyzing brain MRI images. The method employed evaluates brain structural changes over time by assessing the existence probabilities of different brain tissue types, including gray matter, white matter, and cerebrospinal fluid. The dataset used for this study was obtained from the Japanese Alzheimer's Disease Neuroimaging Initiative (J-ADNI). How- ever, limitations include the uncertainty surrounding the onset of Alzheimer's disease in the studied samples, which could potentially impact the classification accuracy, and the study's lack of consideration for the disease's progression during the initial measurement period.

[5] To develop a deep learning (DL) model that

integrates multiple data types (MRI imaging, clinical data, and genetic information) to classify patients into different stages of Alzheimer's disease (AD), including healthy controls (CN), mild cognitive impairment (MCI), and AD. The fusion of data is expected to improve accuracy compared to single- modality models. The study utilizes the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, which includes imaging (MRI), clinical, and genetic (SNP) data from over 2,200 patients across various ADNI studies. However, the small sample size of the ADNI dataset limits the potential of the models, especially in the multi-modality integration scenarios. There is also a challenge in effectively interpreting the complex deep- learning models for clinical decision-making.

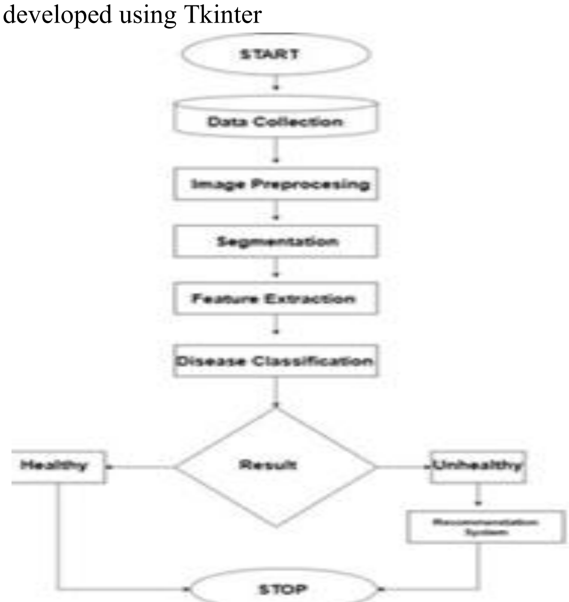
[6] Recent progress in understanding the early stages of Alzheimer's disease (AD), with a focus on the pre-dementia stage known as mild cognitive impairment (MCI). It emphasizes the early cognitive profile and associated neuroimaging studies. The paper does not refer to a specific dataset but dis- cusses' various studies and findings from neuropsychological and neuroimaging research focused on MCI and early AD detection. The paper highlights the difficulty in developing robust criteria for diagnosing MCI and differentiating it from normal aging and other cognitive conditions. Additionally, it points out the challenges in finding early diagnostic markers that are both sensitive and specific.

[7] To investigate retinal alterations in Alzheimer's, dis- ease (AD) patients, explore the associations between retinal changes and AD biomarkers, and develop an optimal machine learning model for diagnosing AD based on retinal thickness measurements. The study included 159 AD patients and 299 healthy controls with data collected through Optical Coherence Tomography (OCT) imaging. The study acknowledges certain limitations, such as the inability to include patients with advanced-stage AD due to the need for cooperation during OCT examinations. Additionally, being a cross-sectional study, it cannot track changes in retinal thickness over time.

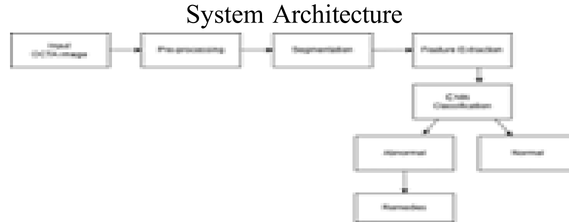
[8] To develop a convolutional neural network (CNN) model to identify Alzheimer's disease (AD) by analyzing multimodal retinal images, including OCT, OCTA, and ultra- widefield (UWF) images, combined with patient data. The dataset included 284 eyes from 159 subjects with 222 eyes from 123 cognitively healthy controls and 62 eyes from 36 subjects with AD. Limitations include the small dataset size,
potential overfitting issues, exclusion of patients with ocular diseases, and limited generalizability. Additionally, UWF im- ages contributed minimally to predictive accuracy, partly due to image quality issues such as eyelid artifacts.

IV. METHODOLOGY

The system architecture for Alzheimer's detection using deep learning consists of five main stages: image input, preprocessing, feature extraction via CNN, classification, and output display. Preprocessing enhances image quality using CLAHE, median filtering, and thresholding to prepare standardized inputs. A trained Convolutional Neural Network (CNN) then extracts features and classifies the image into one of the Alzheimer's stages. Finally, the result is displayed through a user-friendly GUI developed using Tkinter



System Architecture



Activity Diagram

A. Input and Data Collection

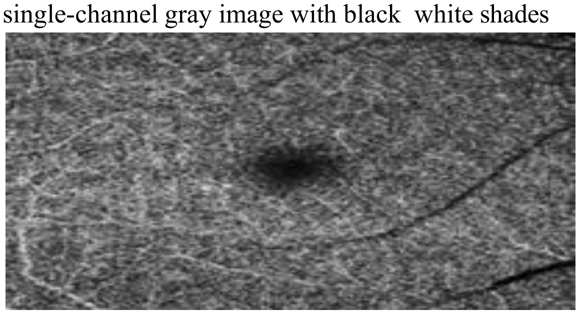
• Input Data: The input consists of OCTA images, which provide detailed visualizations of the retinal microvascular structures. These images are essential for analyzing both vascular and structural properties.

These images are collected from reliable open-source datasets or medical databases and structured in folders where each subfolder corresponds to one of the above classes. This organization enables automatic labeling during processing.

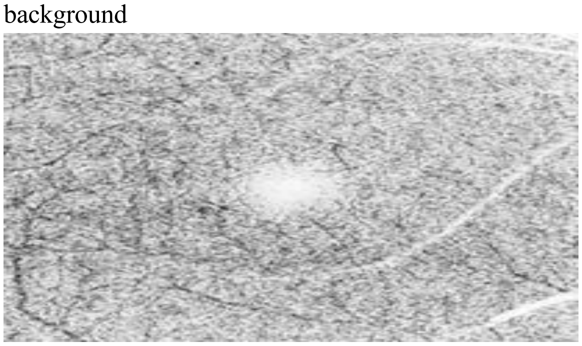
B. Preprocessing

• Image Loading: Read the image from the dataset. Exam- ple: Load an OCTA from deepall/patient001.png

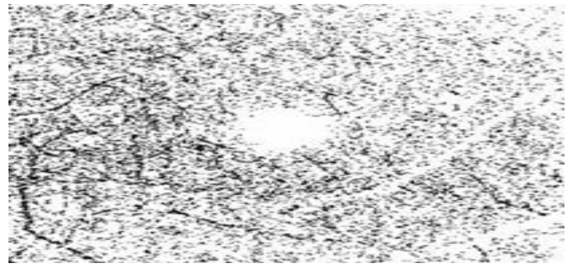
• Convert to Grayscale: Transform the image from RGB (color) to grayscale. Reduces computational complexity and focuses on intensity patterns. Example: A colored OCTA becomes a single-channel gray image with black white shades



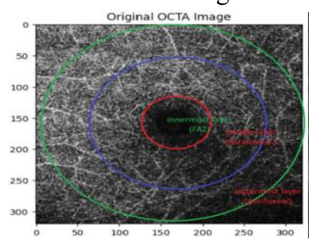
• Inversion: Invert pixel intensities (black becomes white and vice versa). Makes brain structures stand out against the background. Example: If the brain was dark on a light back-ground, after inversion, it becomes light on a dark background

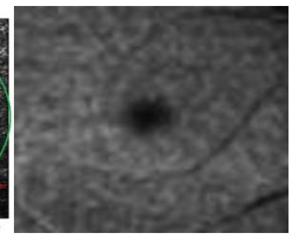


• Thresholding (Binary Inverse): Converts grayscale to black white image. Segments the brain region from background using intensity values. Example: Background becomes black and brain tissues become white, helping in classification.



• Resize the Image: Resize every image to a fixed size (like 50x50). Neural networks require uniform input dimensions. Example: Whether the original MRI is 200x200 or 300x250, it gets resized to 50x50 for training.





C. Segmentation (Implicit)

Although no explicit medical segmentation algorithm is used (e.g., for extracting brain regions), a pseudo-segmentation effect is achieved via:

- CLAHE and Thresholding, which isolate meaningful structures like tissues or patterns by enhancing intensity variations.
- Binary Inversion, which differentiates regions of interest from the background.

This enhances model learning by suppressing irrelevant regions and highlighting informative structures.

D. Feature Extraction

Vascular Area Density: • The proportion of the vascular area (in pixels) within each region is calculated.

$$VAD = \frac{\text{Vascular Pixels}}{\text{Total Pixels in Region}} \times 100\% \qquad (1)$$

Vascular Length Density: • The total length of vessels in each region is calculated by skeletonizing the vascular structures.

• Skeletonization converts the binary vascular mask into 1- pixel-wide representations of the vessels.

$$VLD = \frac{\text{Total Vascular Length}}{\text{Total Area of Region}} \qquad (2)$$

Lower Choriocapillaris Flow Density: • The choriocapillaris layer is isolated by analyzing the lower layers of the OCTA image. • The flow density is computed as the percentage of the area exhibiting blood flow signals.

$$LCFD = \frac{\text{Flow Area}}{\text{Total Area of Region}} \times 100\% \quad (3)$$

- Convolutional Layers extract spatial hierarchies of pat- terns such as edges, textures, and complex structures.
- Pooling Layers reduce dimensionality while preserving key features.
- Fully Connected Layers combine abstract features for decision-making.

E. Disease Classification

A multi-class CNN model is trained using the preprocessed images to classify them into one of four Alzheimer's stages. Model Architecture:

• Input Layer: Accepts 50×50 grayscale images.

• Hidden Layers: Multiple Conv2D and MaxPooling2D layers followed by Dropout and Dense layers.

• Output Layer: A softmax layer with 4 neurons for multi- class classification. Training Details:

• Loss Function: Sparse categorical cross-entropy.
• Optimizer: Adam.
• Validation Split: 10
• Epochs: 20-50(depending on overfitting and underfitting).
• Batch Size: 32. Evaluation:

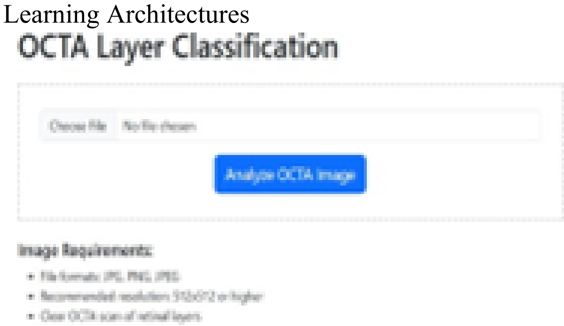
• Accuracy and loss graphs are used to assess training performance.

• Confusion matrix and classification report (precision, recall, F1-score) evaluate the model on test data. Deployment:

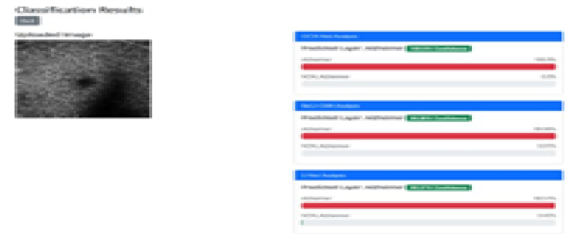
A user-friendly GUI using Tkinter is built to allow users to upload medical images and receive real-time predictions with visual feedback.

F. Output

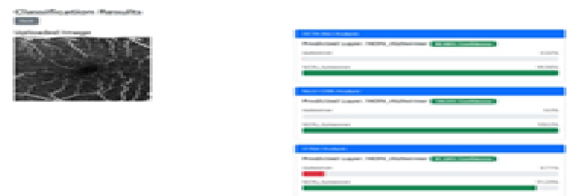
• Model Predictions for Alzheimer's Detection Using ReLU- CNN, U-Net, and OCTA-NetDeep Learning Architectures



OCTA Layer Classification



Classification Result



Classification Result

This output shows the final training results of three deep learning models for Alzheimer's detection.

G. Tools and Technologies

Technologies used: • Programming Language: Python

• Deep Learning Framework: TensorFlow / Keras

• Image Processing Libraries: OpenCV, PIL (Python Imaging Library)

• Model Architecture: Convolutional Neural Networks (CNNs),OCTA $_N$*et, Relu*$_C$*NN, U*$_N$*et*

• Development Environment: VS Code Hardware Require- ments

• Processor: Intel Core i5 or above
• RAM: Minimum 8 GB
• GPU: Optional (Recommended: NVIDIA GPU for faster training)
• Hard disk: 250 GB or more Software requirements
• Operating system: Windows 10 later
• Python: Version 10.0 or above
• Libraries and packages:

o TensorFlow/Keras
o OpenCV
o NumPy
o Matplotlib

• IDE: Visual Studio Code

- Others: CUDA and cuDNN (if GPU acceleration is used)

V. CONCLUSION

This research outlines a comprehensive methodology for processing and analyzing Optical Coherence Tomography Angiography (OCTA) images to extract critical vascular metrics from retinal regions defined by the ETDRS grid. The method utilizes advanced preprocessing techniques, polar coordinate transformations, and the computation of essential indicators such as Vascular Area Density (VAD), Vascular Length Den- sity (VLD), and Lower Choriocapillaris Flow Density (LCFD). These indicators play a crucial role in assessing microvascular integrity and diagnosing retinal conditions such as diabetic retinopathy and macular degeneration.

The workflow from image acquisition to feature extraction and visualization is addressed in a structured manner. Preprocessing steps like image normalization, noise filtering, and segmentation enhance the quality of OCTA scans for accurate analysis. Polar transformations facilitate radial assessment of retinal zones around the Foveal Avascular Zone (FAZ). Mathematical models used to calculate vascular metrics yield consistent, precise insights into the FAZ, perifoveal, and parafoveal regions' health.

The incorporation of deep learning significantly strengthens the framework by automating feature extraction, classification, and prediction tasks. Models such as convolutional neural networks (CNNs) and transformer-based architectures detect complex vascular patterns that may go unnoticed with traditional methods. These models also support scalability and maintain high accuracy across larger datasets.

Findings confirm that deep learning models, when trained on high-quality and properly processed medical imaging data, are powerful tools for aiding early Alzheimer's disease detection. Early diagnosis is vital for initiating timely treatment and may help slow the disease's progression.

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