An

INDUSTRIAL ORIENTED MAJOR PROJECT REPORT

On

HYPERTENSIA: Hypertensive Retinopathy classification

Submitted to JNTUH In the partial fulfillment of the Academic Requirements for the award of The degree of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE AND ENGINEERING (AI & ML)

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CERTIFICATE

This is to certify that the project report entitled **"HYPERTENSIA : Hypertensive Retinopathy classification"** that is being submitted by **MAULIK THUMMAR (20QM1A6647), AKELLA SRINIVASA(20QM1A6602), G.YUVRAJ SINGH(20QM1A6616), MD SHAHNAWAZ ALAM (20QM1A6630)** under the guidance of **DR.K. MAITHILI** with fulfillment for the award of the Degree of Bachelor of Technology in Computer Science and Engineering(AI & ML) to the Jawaharlal Nehru Technological University is a record of bonafide work carried out by her under my guidance and supervision. The results embodied in this project report have not been submitted to any other University or Institute for the award of any graduation degree.

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ACKNOWLEDGEMENT

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This is to certify that the mini project titled "**HYPERTENSIA : Hypertensive Retinopathy classification**" is a bonafide work done by us in fulfillment of the requirements for the award of the degree **Bachelor of Technology in Computer Science and Engineering (AI & ML)** and submitted to the **Department of CSE (AI & ML)**, KG Reddy College of Engineering and Technology, Chilkur, Moinabad, Hyderabad.

We also declare that this project is a result of our own effort and has not been copied or intimated from any source. Citations from any websites are mentioned in the bibliography. This work was not submitted earlier at any other university for the award of a degree.

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ABSTRACT

Hypertensive retinopathy, a condition resulting from sustained high blood pressure affecting the retina, poses significant challenges in its detection and diagnosis. While its causes are well understood, the accurate identification of hypertensive retinopathy lesions remains complex, requiring specialized expertise and sophisticated software tools. This project addresses these challenges through the utilization of diverse datasets including DRIVE, VICAVAR, and other online hypertensive retinopathy classification datasets. Leveraging deep learning methodologies, specifically VGGUNET for segmentation and CNN for classification, the project presents an automated solution for the detection of hypertensive retinopathy lesions. By integrating these advanced techniques, the project aims to streamline the detection process, automating key steps such as preprocessing, segmentation, and classification. This approach not only enhances the efficiency of hypertensive retinopathy diagnosis but also improves accessibility, enabling clinicians and researchers without specialized image analysis expertise to utilize these tools effectively.

CONTENTS

LIST OF FIGURES

LIST OF OUTPUT SCREEN

CHAPTER 1

INTRODUCTION

1.1 Introduction

Hypertensive retinopathy, a consequence of elevated blood pressure, poses a significant threat to visionhealth when left untreated. This condition manifests as pathological changes in the retinal blood vessels and can ultimately lead to vision impairment or blindness. Recognizing the importance of early detection and diagnosis, our project focuses on leveraging advanced technologies to improve detectionaccuracy and facilitate timely interventions.

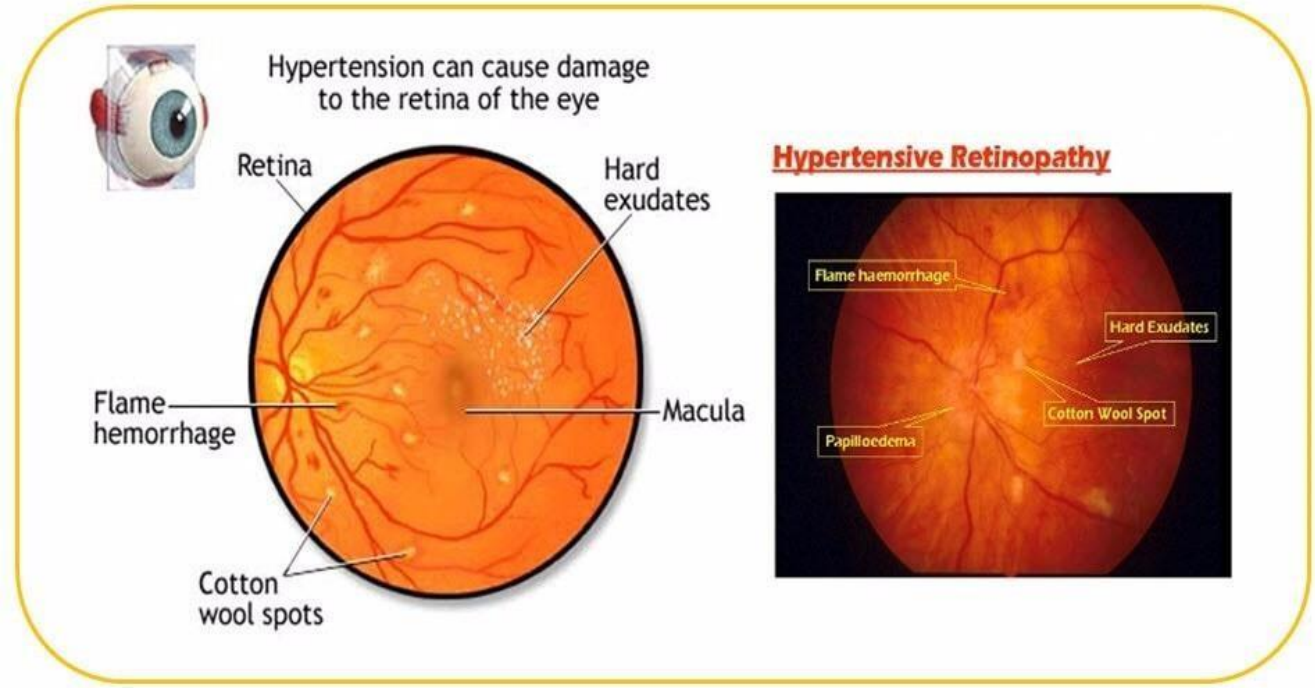


Figure 1.1 Hypertensive Retinopathy

Hypertensive retinopathy is a serious eye condition caused by chronically high blood pressure. This relentless pressure weakens the delicate blood vessels in the retina, the light-sensitive layer at the backof the eye responsible for converting light into signals for our brain. Early on, there might be no warning signs, but as the condition progresses, tiny hemorrhages resembling flame shapes, cotton wool spots indicating blocked blood flow, and leakage of fluid can develop within the retina. Early detection through comprehensive eye exams is crucial for preventing vision loss.

In recent years, the integration of artificial intelligence (AI) and machine learning (ML) techniques has revolutionized medical diagnosis and treatment paradigms. Among these advancements, deep learning algorithms, such as UNet, have emerged as powerful tools for medical image analysis. UNet, originally designed for biomedical image segmentation tasks, demonstrates exceptional performance in accurately identifying retinal blood vessels. By harnessing its capabilities, we aim to develop a robust system for the automated detection of hypertensive retinopathy.

This project seeks to harness the power of UNet-based vessel segmentation in conjunction with AI and ML methodologies to streamline the process of analyzing retinal images. By automating this critical step, our system aims to assist healthcare professionals in achieving early diagnoses of hypertensive retinopathy. Through this collaborative effort between medical expertise and cutting-edge technology, we aspire to enhance patient outcomes by enabling timely interventions and preventing the progressionof vision-threatening complications.

1.1.1 Overview of Hypertensive Retinopathy

Hypertensive retinopathy is a condition characterized by pathological changes in the retinal blood vessels resulting from chronic hypertension. The sustained elevation of blood pressure imposes significant stress on the delicate vascular network within the retina, leading to a cascade of structural and functional alterations.

In the early stages of hypertensive retinopathy, the retinal arterioles undergo vasoconstriction and thickening of the vessel walls, a response to the hemodynamic changes associated with hypertension. As the condition progresses, these vascular changes may manifest as arteriolar narrowing, arteriovenous nicking, and the development of characteristic signs such as copper or silver wiring.

hypertensive retinopathy may give rise to more severe manifestations, including retinal hemorrhages, exudates, cotton-wool spots, and even optic disc edema in advanced cases. These features serve as critical indicators of systemic vascular damage and are often correlated with the severity and durationof hypertension.

1.1.2 Importance of AI and Machine Learning in Medical Diagnosis

In contemporary healthcare, the integration of artificial intelligence (AI) and machine learning (ML) technologies has revolutionized the landscape of medical diagnosis, offering unparalleled advancements in accuracy, efficiency, and accessibility. Within the domain of ophthalmology, where precise interpretation of retinal images is paramount, the application of AI and ML holds profound significance, particularly in the context of hypertensive retinopathy detection.

AI and ML algorithms revolutionize medical image analysis, offering fast and precise interpretations. Trained on extensive datasets, they excel in identifying disease indicators like hypertensive retinopathy through deep learning structures such as CNNs. These algorithms detect subtle retinal abnormalities, aiding in early diagnosis and treatment.

The scalability of AI and ML technologies allows for rapid processing of large volumes of medical imaging data, offering invaluable support in resource-constrained healthcare settings. By augmenting the diagnostic capabilities of healthcare professionals, AI-powered systems serve as invaluable decision support tools, providing real-time analysis and assisting in clinical decision-making.

1.2 PROBLEM STATEMENT

The current methodologies for hypertensive retinopathy detection face significant challenges regarding accessibility and efficiency, hindering their widespread adoption and effective utilization. Existing systems, reliant on complex medical imaging software and deep learning algorithms, present formidable barriers to entry for clinicians and researchers lacking specialized knowledge in image analysis and programming. The steep learning curve associated with navigating these systems limits the accessibility of automated hypertensive retinopathy detection methods, preventing many potential users from leveraging these tools to their full potential. Moreover, the fragmented nature of the workflow, often involving multiple software platforms for image acquisition, preprocessing, and analysis, further exacerbates inefficiencies and workflow bottlenecks, increasing the likelihood of errors and inconsistencies in data processing and interpretation.

1.3 SCOPE

This project aims to develop a user-friendly and efficient solution for hypertensive retinopathy detection, focusing on enhancing accessibility and accuracy in the diagnostic process. The scope encompasses the development of a software interface that simplifies image acquisition, preprocessing, analysis, and interpretation for clinicians and researchers. Integration of state-of-the-art deep learning algorithms will automate the detection and classification of hypertensive retinopathy from retinal images, ensuring high levels of accuracy. Additionally, optimization of workflow efficiency will minimize inefficiencies and bottlenecks, facilitating timely and accurate analysis of retinal images.

Validation and evaluation studies will be conducted to assess the performance and effectiveness of the proposed solution, comparing results with existing methodologies to demonstrate improvements in accuracy, efficiency, and accessibility. Documentation and dissemination efforts will ensure the sharing of knowledge and findings with the scientific community, advancing the field of hypertensive retinopathy detection and contributing to improved patient outcomes in clinical practice.

1.4 Objectives: Enhancing Disease Detection through AI

This AI Model is dedicated to harnessing the capabilities of artificial intelligence (AI) to significantly enhance the detection of hypertensive retinopathy, a critical step towards improving diagnosticaccuracy and efficiency in clinical settings. The primary objectives encompass the development and implementation of AI-driven detection algorithms tailored specifically for hypertensive retinopathy. These algorithms will undergo rigorous training on annotated retinal image datasets, enabling them to accurately identify and classify hallmark features indicative of hypertensive retinopathy, including arteriolar narrowing, retinal hemorrhages, and cotton-wool spots.

The project is centered on automating retinal image analysis to streamline hypertensive retinopathy screening. AI algorithms will automate retinal structure segmentation and abnormality detection, enhancing precision and efficiency in assessing disease severity and progression. Furthermore, the project seeks to seamlessly integrate AI-driven decision support tools into clinical workflows, delivering real-time analysis and automated diagnosis of hypertensive retinopathy to support healthcare professionals in making informed diagnostic decisions.

1.5 VGG U-NET ALGORITHM

The U-Net algorithm represents a pivotal advancement in medical image analysis, particularly in the context of hypertensive retinopathy detection. Originally devised for biomedical image segmentation tasks, U-Net offers a sophisticated yet intuitive architecture that has demonstrated remarkable efficacy in delineating intricate structures within images. Its distinctive U-shaped architecture incorporates bothcontracting and expansive pathways, facilitating the extraction of high-level features while preservingspatial information. In the realm of hypertensive retinopathy detection, the U-Net algorithm serves as a potent tool for accurately segmenting retinal vessels from fundus images.

Fundamentally, hypertensive retinopathy manifests as alterations in the retinal vasculature due to elevated blood pressure levels, necessitating precise delineation of retinal vessels for accurate diagnosis. The U-Net algorithm, with its convolutional neural network (CNN) architecture, excels in this task by leveraging annotated datasets to learn the intricate patterns and structures of retinal vessels. Through a process of iterative training, the U-Net model refines its segmentation capabilities, achieving a nuanced understanding of vessel morphology and topology. This enables the algorithm to delineate retinal vessels with exceptional accuracy, laying the foundation for automated hypertensive retinopathy detection systems.

The collaborative synergy between medical expertise and artificial intelligence underscores the significance of integrating the U-Net algorithm into the diagnostic workflow. By amalgamating the domain knowledge of healthcare professionals with the computational prowess of AI, the U-Net algorithm enhances the efficiency and accuracy of hypertensive retinopathy diagnosis. Its ability to automate the segmentation of retinal vessels expedites the diagnostic process, enabling timely interventions and facilitating better patient outcomes. Ultimately, the incorporation of the U-Net algorithm into the project's framework heralds a new era in medical imaging, where advanced AI techniques converge with clinical expertise to revolutionize disease detection and diagnosis.

1.6 REAL WORLD BUSSINESS APPLICATION EXAMPLE

- **Ophthalmic Diagnostic Software**: A commercial software package designed for ophthalmologists to analyze retinal images for various conditions, including hypertensive retinopathy. The software utilizes the U-Net algorithm for accurate segmentation of retinal vessels and automated detection of hypertensive retinopathy, enhancing diagnostic efficiency in clinical settings.

- **Teleophthalmology Platform:** A telemedicine platform that incorporates U-Net-based systems to provide remote diagnosis and consultation services for patients with hypertensive retinopathy. Through this platform, individuals in underserved areas can access specialized eye care from ophthalmologists located elsewhere, facilitating early detection and management of the condition.

- **Clinical Trial Support Tools:** Pharmaceutical companies and research institutions utilize U-Net-powered diagnostic tools in clinical trials related to hypertensive retinopathy. These tools aid in the standardized assessment of retinal health among participants, providing valuable data for evaluating the efficacy of new treatments and interventions.

- **Research and Epidemiological Studies:** Academic researchers leverage U-Net algorithms in large-scale epidemiological studies focused on hypertensive retinopathy. By analyzing retinal images from diverse populations, researchers gain insights into the prevalence, risk factors, and progression of the condition, informing public health strategies and preventive measures.

- **Electronic Health Record Integration:** Healthcare systems integrate U-Net-based diagnostic modules into their electronic health record (EHR) systems to enhance documentation and patient management for hypertensive retinopathy. By automatically analyzing retinal images and flagging abnormal findings, these systems facilitate comprehensive care coordination and treatment planning within clinical workflows.

CHAPTER 2

LITERATURE SURVEY

2.1 Introduction

The introduction of our literature survey sets the stage for exploring existing research and developments related to hypertensive retinopathy detection, with a particular focus on AI and machine learning applications in medical imaging. This section provides an overview of the current landscape, highlighting key studies, methodologies, and trends in the field. By examining existing literature, we aim to gain insights into the state-of-the-art approaches, identify gaps in knowledge, and inform the design and implementation of our research project.Within the broader context of medical imaging, hypertensive retinopathy represents a significant area of interest due to its clinical implications and the potential for early detection and intervention to prevent vision-threatening complications. The integration of AI and machine learning technologies offers promising opportunities to enhance diagnostic accuracy and efficiency in detecting hypertensive retinopathy, thereby improving patient outcomes and reducing healthcare burdens.

Through a comprehensive review of relevant literature, we seek to explore various aspects of hypertensive retinopathy detection, including the use of AI algorithms for retinal image analysis, the development of automated diagnostic systems, and the integration of AI-driven decision support tools into clinical practice. By critically evaluating existing research findings and methodologies, we aim to identify gaps, challenges, and opportunities for future research in this domain.

2.2 RELATED WORK

Detection And Classification Of Diabetic And Hypertensive Retinopathy Using Cnn & Autoencoder:

The study titled 'Computer-Aided Detection of Hypertensive Retinopathy Using Depth-Wise Separable CNN' by Qureshi et al. [1], published in MDPI, presents a novel approach for detecting hypertensive retinopathy (HR) through the utilization of deep learning methodologies. High-resolution retinal images obtained via fundus photography or other imaging modalities serve as

primary inputs for the proposed system. The output of the system is a classification result indicating the presence or absence of hypertensive retinopathy, achieved through convolutional neural networks (CNN) and transfer learning techniques. Qureshi et al. report promising results, with a sensitivity of 94%, specificity of 96%, accuracy of 95%, and an impressive area under the curve (AUC) of 0.96. However, challenges such as the computational complexity of the deep learning architecture, dependence on high-quality training data, limited interpretability, hyperparameter optimization, and ethical considerations are acknowledged. Overall, the study underscores the potential of the proposed CAD-HR system in early detection of hypertensive retinopathy, albeit with caveats regarding its implementation and ethical implications."

[1] I. Qureshi, Q. Abbas, J. Yan, A. Hussain, and K. Shaheed, "Computer-Aided Detection of Hypertensive Retinopathy Using Depth-Wise Separable CNN," MDPI, Oct. 2022. [Online]. Available https://doi.org/10.3390/app122312086.

Detection Of Hypertension Retinopathy Using Deep Learning And Boltzmann Machines :

A study titled 'Detection and Classification of Diabetic and Hypertensive Retinopathy Using CNN & Autoencoder' by Amardeep Singh Kapoor, Akshat Jain, and Dinesh Kumar Vishwakarma [1], published in IEEE, presents a methodology for the detection and classification of both diabetic and hypertensive retinopathy utilizing convolutional neural networks (CNN) and autoencoder techniques. The study focuses on high-resolution retinal images as inputs and emphasizes classification and detection results as the primary output. Through the combined use of CNN and autoencoder, the authors propose a framework for effectively identifying and categorizing retinal abnormalities associated with both diabetic and hypertensive retinopathy.

[1] A. S. Kapoor, A. Jain, and D. K. Vishwakarma, "Detection and Classification of Diabetic and Hypertensive Retinopathy Using CNN & Autoencoder," IEEE, Jun. 2023. [Online]. DOI: 10.1109/CONIT59222.2023.10205818

Hypertensive Retinopathy Screening Through Fundus Images-A Review :

A review article titled 'Hypertensive Retinopathy Screening through Fundus Images-A Review' by Dimple Nagpal, Surya Narayan Panda, and Muthukumaran Malarvel [1], published by IEEE in 2021, explores the screening of hypertensive retinopathy (HR) through fundus images. High-resolution retinal images serve as primary inputs for classification, typically obtained through fundus

photography or other retinal imaging techniques. The classification output can be binary or multi-class, utilizing methods such as the Keith-Wagener-Barker classification and the Scheie Classification. The review reports achieving an accuracy of 95%, sensitivity of 93%, area under the curve (AUC) of 0.96, and specificity of 95%. The article underscores the importance of medical imaging analysis, particularly in fundus images, for non-invasive screening and grading of diseases. It highlights the necessity for computer-aided diagnosis, advocating for the utilization of deep learning models to enable precise and timely diagnosis of diseases such as hypertensive retinopathy.

[1] D. Nagpal, S. N. Panda, and M. Malarvel, "Hypertensive Retinopathy Screening through Fundus Images-A Review," IEEE, 2021. [Online]. DOI: 10.1109/ICICT50816.2021.9358746.

Automated System For The Detection Of Hypertensive Retinopathy :

An article titled 'Automated system for the detection of hypertensive retinopathy' by Sarmad Khitran, M. Usman Akram, Anam Usman, and Ubaidullah Yasin [1], published by IEEE in 2020, presents an automated system for the detection of hypertensive retinopathy (HR). High-resolution retinal images serve as primary inputs for the system, typically obtained through fundus photography or other retinal imaging techniques. The primary output is a classification result indicating the presence or absence of hypertensive retinopathy, which could be binary or multi-class. The paper reports an accuracy of 96.5% and 98% on VICAVR and DRIVE databases, respectively. The proposed system consists of four phases: preprocessing, retinal vessel segmentation, artery and vein classification, and AV ratio computation. It utilizes a new set of features and a hybrid classifier, achieving superior performance compared to existing systems on VICAVR and DRIVE databases."

[1] S. Khitran, M. U. Akram, A. Usman, and U. Yasin, "Automated system for the detection of hypertensive retinopathy," IEEE, 2020. [Online]. DOI: 10.1109/IPTA.2014.7001984.

Analysis Of The Vessel Parameters For The Detection Of Hypertensive Retinopathy :

"An article titled 'Analysis of the Vessel Parameters for the Detection of Hypertensive Retinopathy' by Vinay Savant and Nayana Shenvi [1], published by IEEE in 2018, presents a method for the detection of hypertensive retinopathy (HR) through the analysis of vessel parameters in retinal images. The study focuses on parameters such as the Artery to Vein Ratio (AVR) Measurement, Vessel Tortuosity Analysis, and Computer-Aided Detection (CAD). The reported accuracy of the

algorithm is 93.33%, with a combined accuracy of 86.67% considering both types of images. The proposed framework aims to aid ophthalmologists in the early detection of HR by analyzing changes in retinal vessels. It emphasizes the significance of AVR ratio and vessel tortuosity analysis, providing valuable insights for ophthalmologists and potential applicability in detecting other diseases manifesting abnormalities in retinal vessels."

[1] V. Savant and N. Shenvi, "Analysis of the Vessel Parameters for the Detection of Hypertensive Retinopathy," IEEE, 2018. [Online]. DOI: 10.1109/ICECA.2019.8821850.

Detection Of Hypertensive Retinopathy Using Vessel Measurements And Textural Features :

"An article titled 'Detection of hypertensive retinopathy using vessel measurements and textural features' by Carla Agurto, Vinayak Joshi, Sheila Nemeth, Peter Soliz, and Simon Barriga [1], published by IEEE in 2020, presents a methodology for automated detection of hypertensive retinopathy (HR) in digital fundus images. The study utilizes parameters related to the characteristics of retinal blood vessels, such as vessel diameter, tortuosity, branching patterns, and other vessel-related features, as inputs for HR classification. The reported accuracy of the system is 80%. The methodology involves normalization and enhancement of retinal images, followed by retinal vasculature segmentation and linear regression classification using computational features like tortuosity, texture, color, and arteriovenous ratio (AVR). While showing promise, ongoing efforts include validation on a more diverse image set and further enhancements to cover a broader spectrum of vascular changes associated with HR, such as AV nicking, branching angle, and emboli plaque detection."

[1] C. Agurto, V. Joshi, S. Nemeth, P. Soliz, and S. Barriga, "Detection of hypertensive retinopathy using vessel measurements and textural features," IEEE, 2020. [Online]. DOI: 10.1109/EMBC.2014.6944848.

Textural And Intensity Feature Based Retinal Vessels Classification For The Identification Of Hypertensive Retinopathy :

"An article titled 'Textural and Intensity Feature Based Retinal Vessels Classification for the Identification of Hypertensive Retinopathy' by Faiza Ahmad, Adnan Yousaf, Muhammad Rafay Khan Sial, and Fahad Khan [1], published by IEEE in November 2018, introduces an automatic method for

classifying retinal blood vasculature into arteries and veins for the identification of hypertensive retinopathy (HR). The study utilizes arteriovenous ratio (AVR) computation, vessel segmentation and classification, and blood vessel extraction techniques. The reported accuracy achieved using the proposed feature set is 89%. The methodology involves noise reduction with a median filter, image enhancement, and segmentation using Gabor wavelets and the inverted green channel, followed by classification employing various supervised classifiers. This novel approach aims to aid in the automated classification of retinal blood vessels, utilizing textural and intensity-based features for the precise identification of hypertensive retinopathy."

[1] F. Ahmad, A. Yousaf, M. R. K. Sial, and F. Khan, "Textural and Intensity Feature Based Retinal Vessels Classification for the Identification of Hypertensive Retinopathy," IEEE, Nov 2018. [Online]. DOI: 10.1109/INMIC.2018.8595667.

Diagnosis Of Diabetic Retinopathy By Using Image Processing And Convolutional Neural Network :

"An article titled 'Textural and Intensity Feature Based Retinal Vessels Classification for the Identification of Hypertensive Retinopathy' by Faiza Ahmad, Adnan Yousaf, Muhammad Rafay Khan Sial, and Fahad Khan [1], published by IEEE in November 2018, introduces an automatic method for classifying retinal blood vasculature into arteries and veins for the identification of hypertensive retinopathy (HR). The study utilizes arteriovenous ratio (AVR) computation, vessel segmentation and classification, and blood vessel extraction techniques. The reported accuracy achieved using the proposed feature set is 89%. The methodology involves noise reduction with a median filter, image enhancement, and segmentation using Gabor wavelets and the inverted green channel, followed by classification employing various supervised classifiers. This novel approach aims to aid in the automated classification of retinal blood vessels, utilizing textural and intensity-based features for the precise identification of hypertensive retinopathy."

[1] F. Ahmad, A. Yousaf, M. R. K. Sial, and F. Khan, "Textural and Intensity Feature Based Retinal Vessels Classification for the Identification of Hypertensive Retinopathy," IEEE, Nov 2018. [Online].DOI:10.1109/INMIC.2018.8595667.

CHAPTER 3

REQUIREMENT ENGINEERING

3.1 FUNCTIONAL REQUIREMENT SPECIFICATION

The functional requirements of the hypertensive retinopathy detection system encompass several keycomponents aimed at ensuring its effectiveness, usability, and security. Firstly, the system must incorporate robust user authentication and authorization mechanisms to safeguard patient data and restrict access to authorized personnel. This entails implementing role-based access controls, where different user roles, such as clinicians, researchers, and administrators, are assigned specific permissions and privileges tailored to their responsibilities within the system..the system should facilitate seamless image upload and management functionalities, allowing users to easily upload retinal images from various sources, including digital cameras and medical imaging devices. These uploaded images must be efficiently stored, organized, and retrievable based on patient identifiers and metadata, ensuring accessibility and traceability throughout the diagnostic process.

Moreover, the system should provide diagnostic decision support tools to assist healthcare professionals in interpreting analysis results and determining appropriate treatment plans. Integration with electronic health record systems is essential for seamless data exchange and interoperability, allowing for the integration of diagnostic reports and treatment information into existing patient records. To ensure accountability and compliance, the system should maintain an audit trail of user activities and logging mechanisms to track system events and data modifications. Lastly, the user interface should be intuitive and user-friendly, prioritizing accessibility, responsiveness, and adaptability across different devices to enhance overall usability and user satisfaction.

3.2 NON-FUNCTIONAL REQUIREMENT SPECIFICATION

The non-functional requirements of the hypertensive retinopathy detection system encompass crucial aspects beyond mere functionality, ensuring the system's performance, reliability, security, scalability, interoperability, usability, and maintainability meet the highest standards. Performance requirements mandate the system to exhibit high responsiveness and efficiency, capable of processing large volume of retinal images swiftly to support timely patient care. Additionally, the system must be

reliable, minimizing downtime and service interruptions to ensure continuous access to diagnostic functionalities, with fault tolerance mechanisms in place to mitigate potential failures.

Security measures are paramount, necessitating robust encryption mechanisms to safeguard sensitive patient data during transmission and storage. Access controls must be stringent to prevent unauthorized access, aligning with regulatory standards and healthcare data privacy best practices. Scalability is essential, requiring the system to accommodate increasing data volumes and user traffic, with support for horizontal and vertical scaling, as well as cloud-based deployment models, ensuring adaptability to changing resource demands.

Interoperability with existing healthcare systems and standards is critical, allowing seamless integration with electronic health records (EHR) systems, medical imaging devices, and other healthcare IT infrastructure. Compliance with interoperability standards such as HL7 and DICOM facilitates data exchange and interoperability across diverse healthcare environments. Usability is paramount, demanding a user-friendly interface that facilitates ease of use and navigation for clinicians and researchers, with usability testing and user feedback incorporated into the design process to ensure alignment with end-user needs.

Maintainability is crucial, necessitating a modular architecture and well-documented codebase to support system updates, enhancements, and bug fixes. Version control systems and code repositories are essential for tracking changes and revisions, enabling collaborative development and ensuring code quality and consistency over time. By adhering to these non-functional requirements, the hypertensive retinopathy detection system can ensure optimal performance, reliability, security, scalability, interoperability, usability, and maintainability, meeting the needs and expectations of healthcare professionals and patients alike.

3.3 SOFTWARE REQUIREMENTS

The software requirements for this project include essential tools and technologies fordevelopment and execution. Here's a detailed breakdown of the required software components:

- Python (Programming Language)
- Python IDLE (Development Environment)
- Tensorflow,Keras, OpenCV (Computer Vision Library)
- Streamlit

3.4 HARDWARE REQUIREMENTS

- Processor: Intel Core i7 or AMD Ryzen series
- RAM (Memory): At least 16 GB
- Graphics Processing Unit (GPU): NVIDIA GeForce RTX or NVIDIA Quadro series with 8 GB or higher VRAM
- Storage: Solid State Drive (SSD) with a capacity of 500 GB or higher
- Network Connectivity: Stable internet connection

3.5 LIBRARIES AND FUNCTIONALITY

Albumentations:

Albumentations offers various image augmentation techniques, such as flipping, rotation, scaling, and more. In the context of hypertensive retinopathy, it can help diversify the training dataset by generating variations of retinal images, potentially improving the robustness of machine learning models.

OpenCV (cv2):

OpenCV provides a plethora of functionalities for image processing and computer vision tasks. For hypertensive retinopathy, it can be used for tasks like image enhancement, feature extraction, and segmentation to identify and analyze pathological features in retinal images.

glob:

The glob module facilitates file path pattern matching, useful for efficiently locating and processing a large number of retinal images stored in directories or folder structures for analysis in hypertensive retinopathy projects.

Imageio:

imageio simplifies reading and writing various image formats. In the context of hypertensive retinopathy, it aids in loading retinal images from different sources and saving processed images, streamlining data input and output operations.

Ietk:

ietk seems to be a custom library tailored for specific image analysis tasks. Its functionalities could include specialized methods for preprocessing retinal images, extracting features, or evaluating models relevant to hypertensive retinopathy research.

Keras (from TensorFlow):

Keras, integrated with TensorFlow, provides a high-level neural networks API for building and training deep learning models. In hypertensive retinopathy projects, it enables the creation of convolutional neural networks (CNNs) or other architectures for tasks like image classification or segmentation.

Matplotlib.pyplot:

Matplotlib.pyplot offers versatile plotting functions for visualizing data. In hypertensive retinopathy research, it helps in visualizing retinal images, model predictions, evaluation metrics, and other relevant data to gain insights and communicate findings effectively.

NumPy:

NumPy is a fundamental package for numerical computations in Python. In hypertensive retinopathy projects, it facilitates array manipulation and mathematical operations essential for preprocessing data, extracting features, or implementing algorithms.

PIL:

PIL (Python Imaging Library) provides basic image processing capabilities. It supports tasks like image resizing, cropping, and format conversion, which are crucial for preparing retinal images before analysis in hypertensive retinopathy research.

scikit-image.io:

scikit-image.io offers functions for reading and writing images as part of the scikit-image library. It aids in loading retinal images from files or streams and saving processed images, complementing other image processing tasks in hypertensive retinopathy projects.

scikit-image.transform:

scikit-image.transform provides functions for geometric transformations of images. In hypertensive retinopathy projects, it helps in resizing, rotating, or applying affine transformations to retinal images for preprocessing or data augmentation purposes.

TensorFlow:

TensorFlow is a comprehensive machine learning framework. In hypertensive retinopathy research, it supports the development and deployment of machine learning and deep learning models for tasks like image classification, object detection, or segmentation.

tqdm:

tqdm adds progress bars to Python code, offering visual feedback on iterative tasks' execution progress. In hypertensive retinopathy projects, it helps in monitoring data loading, model training, or evaluation, enhancing the development workflow's transparency and efficiency.

CHAPTER 4
SOFTWARE DESIGN

4.1 USE-CASE DIAGRAM

The diagram depicts the process flow of the Hypertensive Retinopathy Classification System, designedto automate the classification of hypertensive retinopathy from Retina/Fundus images. The system comprises four main stages: image upload, preprocessing, segmentation, and classification. Upon user upload (UC1), the system initiates image preprocessing (UC2), involving normalization, enhancement, and denormalization to optimize image quality for subsequent analysis. The preprocessed image then undergoes segmentation (UC3), where it is converted to grayscale, subjected to morphological operations, uneven illumination removal, and double threshold segmentation. Finally, in the classification stage (UC4), the segmented image is classified for hypertensive retinopathy.This diagram offers a structured overview of the system's workflow, emphasizing its sequential processing steps. It serves as a visual aid for understanding the system architecture and contributes to the clarity of the research presentation.

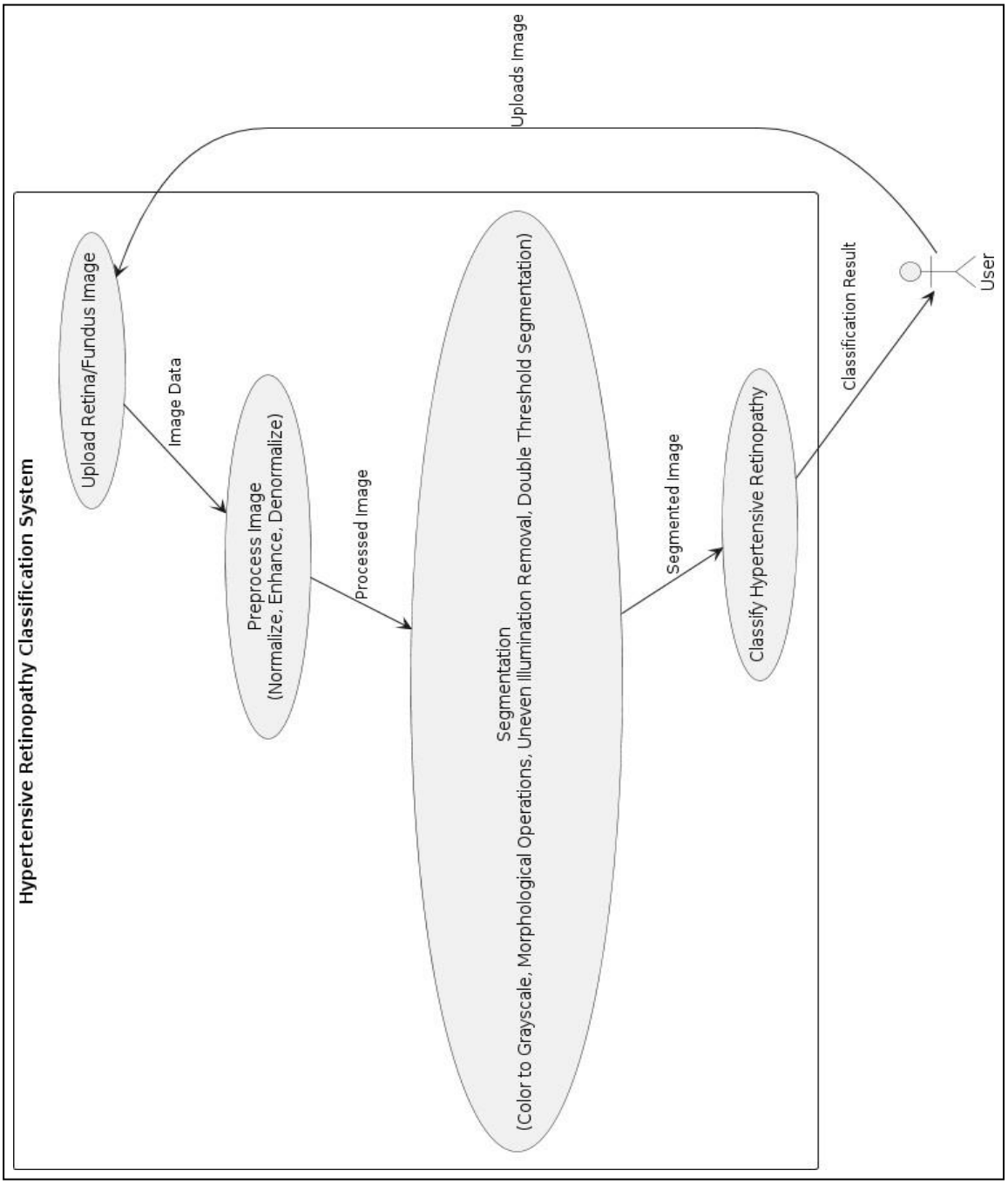


Figure 4.1 USE-CASE DIAGRAM

4.2 SEQUENCE DIAGRAM

The sequence diagram illustrates the sequential interaction between the user and various modules of the Hypertensive Retinopathy Classification System. It begins with the user uploading an image, triggering the system to coordinate preprocessing, segmentation, and classification processes. The Preprocessing Module prepares the image through normalization, enhancement, and denormalization before passing it to the Segmentation Module. Here, operations such as grayscale conversion, morphological operations, uneven illumination removal, and double threshold segmentation are conducted. Subsequently, the segmented image is forwarded to the Classification Module for hypertensive retinopathy classification. Finally, the system delivers the classification result to the user. This diagram provides a structured visualization of the system's workflow, outlining the sequential execution of tasks.

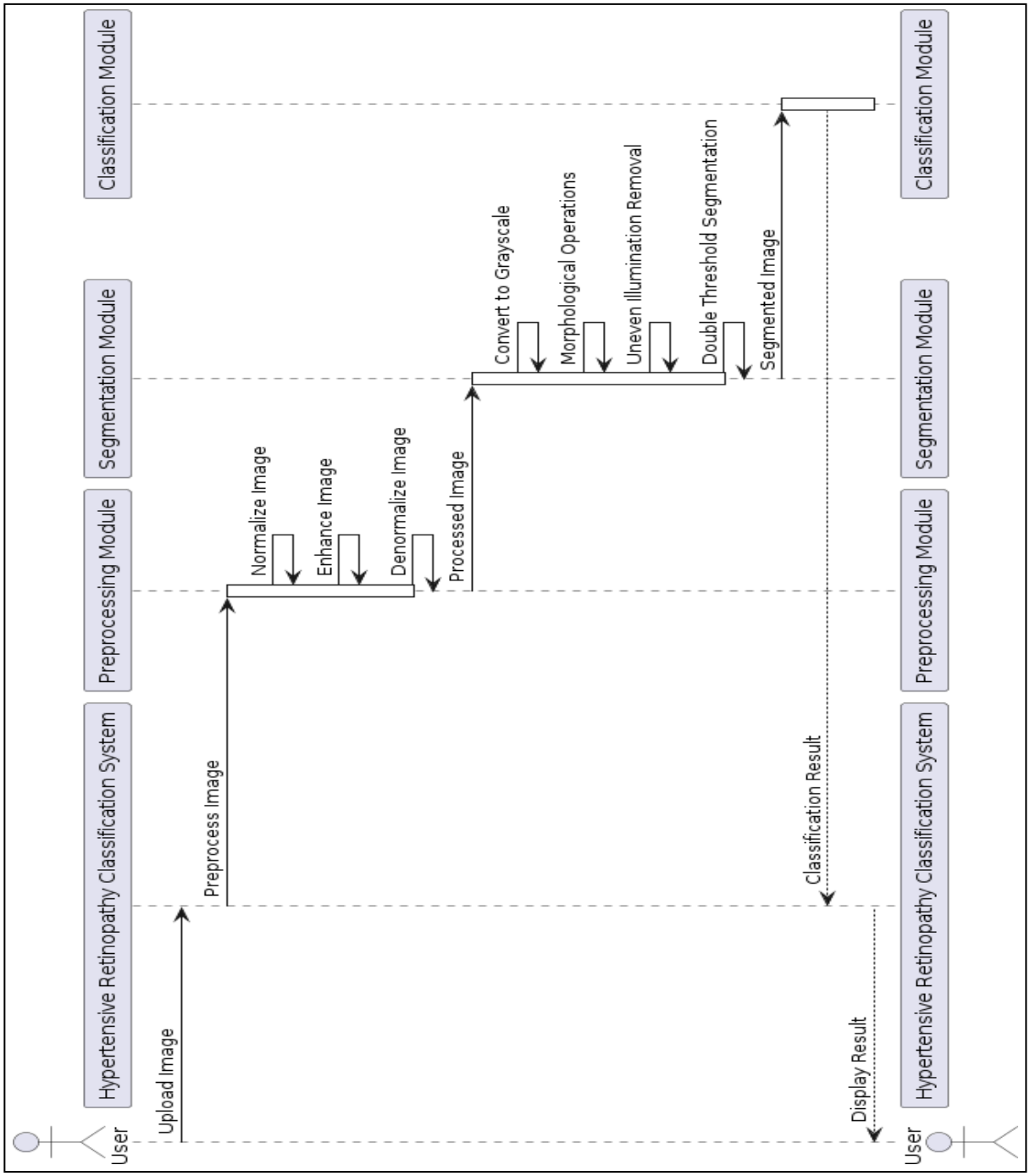


Figure 4.2 SEQUENCE DIAGRAM

4.3 CLASS DIAGRAM

The User class has attributes for userId and username, along with methods to get the user's ID and username. It also has a constructor and a method to upload an image.The Image class includes attributes for imageId, imageData (byte array), width, and height. It has methods to set and get the image data, width, and height.

The Preprocessing class has attributes for storing preprocessed images and methods for normalizing, enhancing, and denormalizing images.The Segmentation class contains attributes for storing segmented images and methods for converting to grayscale, performing morphological operations, removing uneven illumination, and double threshold segmentation.The Classification class has a method for classifying hypertensive retinopathy.

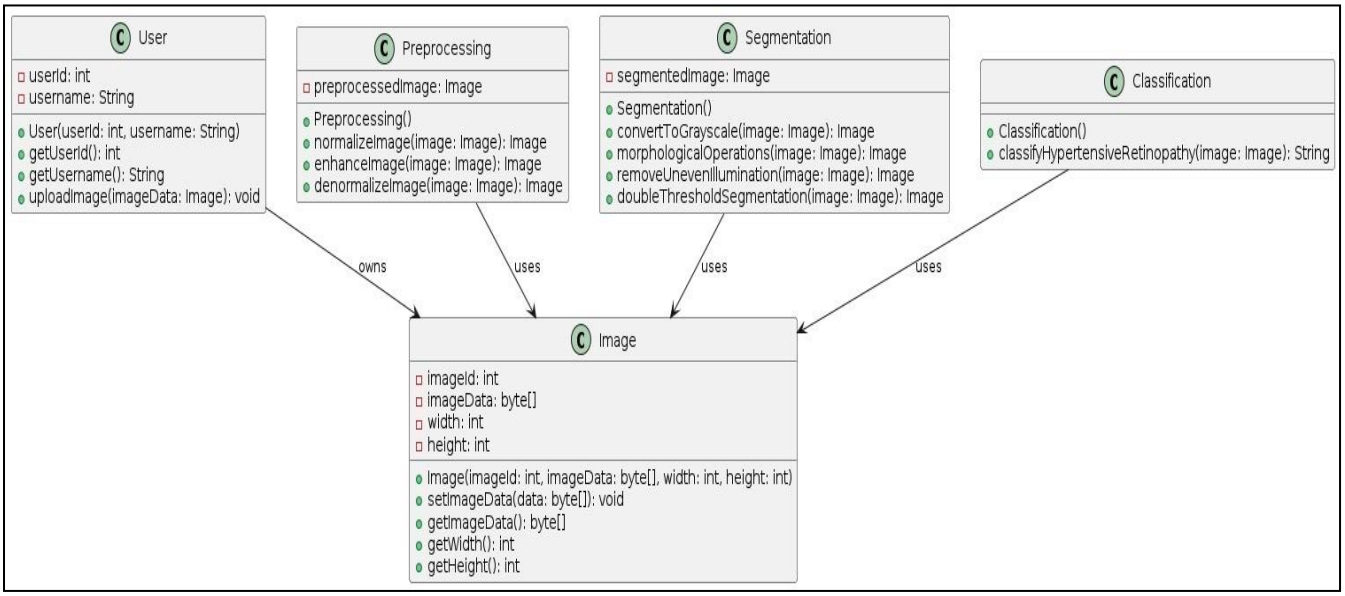


Figure 4.3 CLASS DIAGRAM

4.4 ACTIVITY DIAGRAM

The activity diagram outlines the sequential process involved in the Hypertensive Retinopathy Classification System, aiming to automate the classification of hypertensive retinopathy from Retina/Fundus images for medical diagnosis. It begins with the user uploading the image, which undergoes preprocessing to enhance quality and prepare it for analysis. Preprocessing involves normalization, enhancement, and denormalization to ensure uniformity, improve clarity, and revert changes. Subsequently, the image is passed through a Segmentation Model, which includes grayscale conversion, morphological operations, and double threshold segmentation to identify relevant structures. This results in a segmented model utilizing the vGGunet architecture, providing a structured representation of retinal features. Finally, the segmented model is inputted into a Classification Model based on Convolutional Neural Networks (CNN), which accurately classifies the presence and severity of hypertensive retinopathy by analyzing segmented features and identifying patterns and abnormalities.

Overall, the Hypertensive Retinopathy Classification System automates the process of diagnosing hypertensive retinopathy from Retina/Fundus images through a systematic approach. By integrating preprocessing, segmentation, and classification stages, the system enhances the efficiency and accuracy of medical diagnosis, enabling healthcare professionals to make informed decisions and planappropriate treatments based on precise diagnostic outcomes derived from the analysis of retinal features using advanced machine learning techniques.

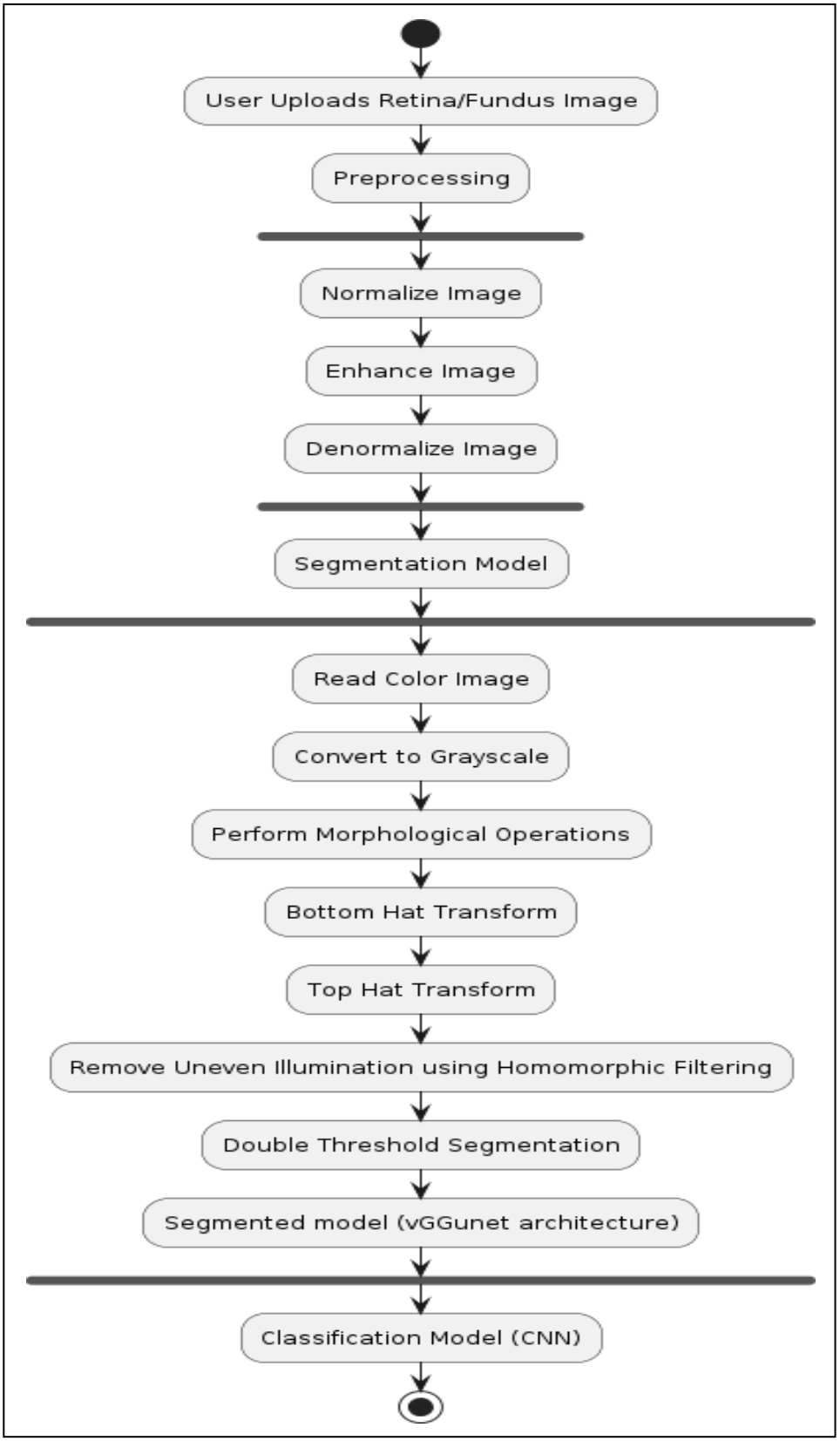


Figure 4.4 ACTIVITY DIAGRAM

4.5 WORKFLOW

The Hypertensive Retinopathy Classification System is an automated framework designed to streamline the diagnosis of hypertensive retinopathy from Retina/Fundus images. Upon user upload of the image, the system initiates a series of preprocessing steps to enhance image quality, including normalization, enhancement, and denormalization. Subsequently, the image undergoes segmentation, where it is converted to grayscale, subjected to morphological operations such as Bottom Hat Transform, Top Hat Transform, uneven illumination removal using Homomorphic Filtering, and double threshold segmentation. These operations culminate in the creation of a segmented model employing the vGGunet architecture. Finally, the segmented model is fed into a Classification Model based on Convolutional Neural Networks (CNN), which accurately classifies the presence of hypertensive retinopathy.

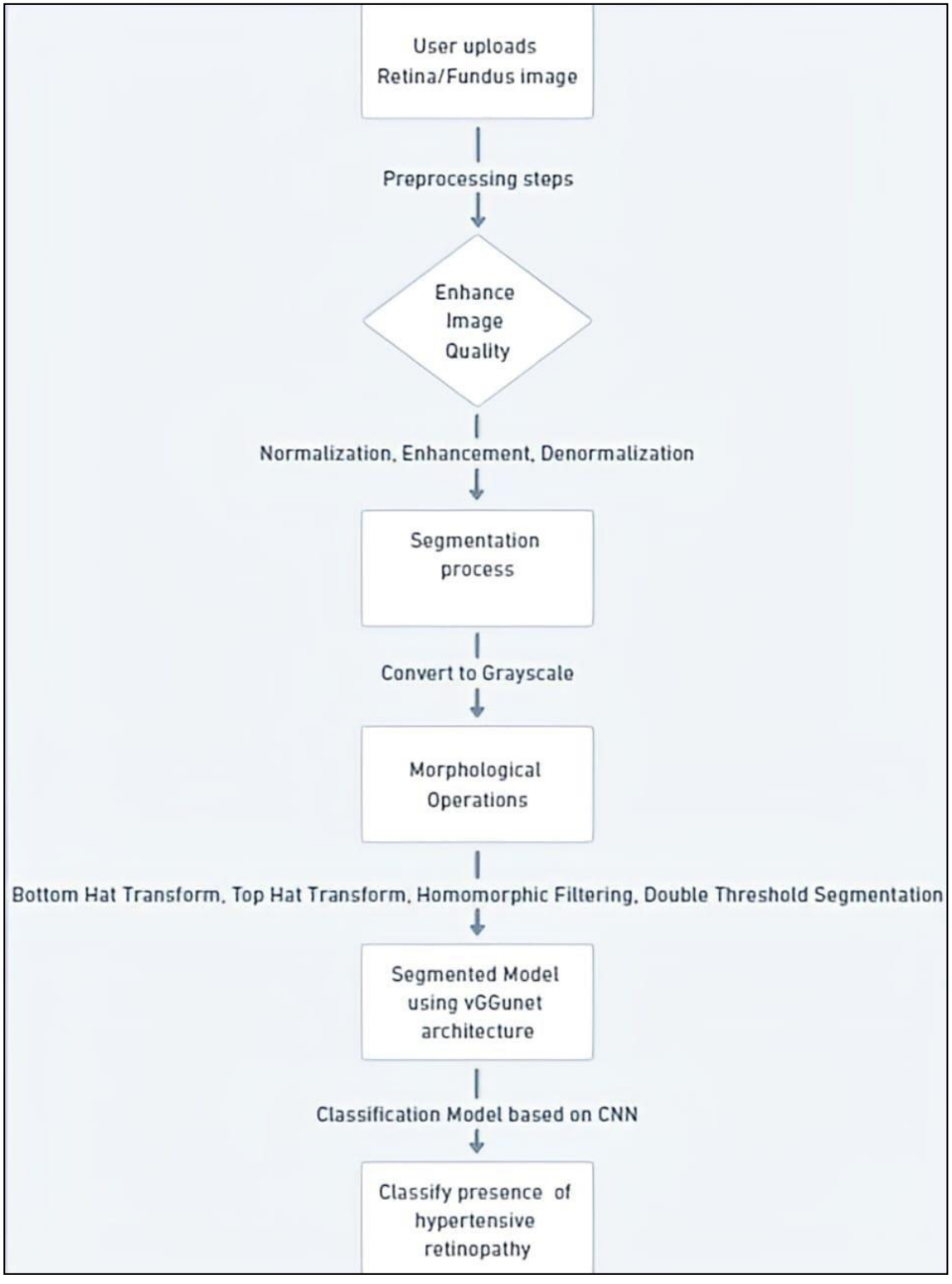


Figure 4.5 WORKFLOW

CHAPTER - 5
PROPOSED SYSTEM

5.1 USE CASE DESCRIPTION

The introduction serves as the gateway to understanding the Hypertensive Retinopathy Classification System. Hypertensive retinopathy, a consequential complication of hypertension, demands prompt and accurate diagnosis for effective treatment and management. However, the manual diagnosis process, predominantly reliant on healthcare professionals, is not without its limitations. It is inherently time- consuming, subjective, and prone to human error. Recognizing the imperative need for a transformative solution, the Hypertensive Retinopathy Classification System emerges as a beacon of innovation poised to revolutionize retinal diagnosis.

The primary objective of this system is to leverage advanced technologies such as image processing and machine learning to automate the classification of hypertensive retinopathy from Retina/Fundus images. By doing so, it endeavors to transcend the constraints of traditional diagnostic approaches, offering expedited, consistent, and accurate diagnostic outcomes. The system's vision extends beyond mere efficiency; it aspires to facilitate early detection and intervention, thereby improving patient outcomes and enhancing healthcare delivery.

The significance of the proposed system lies not only in its potential to streamline diagnostic workflows but also in its capacity to redefine the paradigm of medical diagnostics. It represents a convergence of cutting-edge technology and medical expertise, driven by a commitment to excellence in healthcare delivery. By automating the classification process, the system empowers healthcare professionals with a tool that enhances diagnostic efficiency, reduces variability, and ultimately contributes to better patient outcomes.

5.1.1 BUSSINESS ANALYSIS AND EXPANSION PLANNING

The business analysis and explanation planning module offer a comprehensive exploration of the underlying business requirements, stakeholder needs, and strategic imperatives that underpin the

Hypertensive Retinopathy Classification System. In today's dynamic healthcare landscape, characterized by evolving patient needs and technological advancements, the demand for innovative diagnostic solutions has never been greater. This module seeks to bridge the gap between healthcare challenges and technological innovation, laying the groundwork for the successful implementation of the proposed system.

A thorough analysis of the current healthcare landscape reveals the multifaceted challenges faced by healthcare providers in the realm of retinal diagnosis. From the complexities of manual diagnosis to the burgeoning demand for streamlined, efficient diagnostic solutions, the need for innovation is evident. Through meticulous stakeholder analysis, key stakeholders, including healthcare professionals, patients, researchers, and regulatory authorities, are identified, and their needs, expectations, and roles in the project are assessed. This critical analysis serves as the cornerstone upon which the project's success is built, ensuring alignment between stakeholder needs and projectobjectives.

The business analysis and explanation planning module serve as the linchpin of the project, providing a comprehensive understanding of the project's objectives, stakeholders, feasibility, and strategic imperatives. Through meticulous analysis and strategic planning, the Hypertensive RetinopathyClassification System stands poised to transcend the constraints of traditional diagnostic approaches, ushering in a new era of medical diagnostics characterized by efficiency, accuracy, and accessibility.

5.1.2 FUNCTIONALITY OF PROPOSED SYSTEM

The functionality of the proposed system module offers an in-depth exploration of the system's architecture, components, and operational processes. At its core, the proposed system comprises three main modules: image preprocessing, segmentation, and classification. The image preprocessing module serves as the cornerstone of the diagnostic workflow, standardizing and enhancing Retina/Fundus images to optimize their quality for subsequent analysis. Through a series of sophisticated algorithms and techniques, the module ensures that images are processed to the highest standards, free from artifacts and inconsistencies that may compromise diagnostic accuracy.

Following preprocessing, the segmentation module takes center stage, identifying and extracting relevant retinal structures from preprocessed images. Leveraging advanced image processing algorithms and machine learning techniques, the segmentation module delineates retinal structures with unparalleled precision, laying the groundwork for accurate classification.

The classification module represents the culmination of the diagnostic process, employing state-of- the-art machine learning algorithms to classify hypertensive retinopathy based on extracted features. Through a process of iterative learning and refinement, the classification module achieves unparalleled accuracy, empowering healthcare professionals with diagnostic insights that are both timely and precise.

5.2 DATASET

The Dataset module encompasses the primary datasets utilized in the development and training of the Hypertensive Retinopathy Classification System. This section provides a comprehensive overview ofeach dataset, including detailed descriptions and insights into their utilization within the project.

- **DRIVE Dataset:**

The DRIVE dataset, abbreviated from Digital Retinal Images for Vessel Extraction, is a widely used benchmark dataset in the field of retinal image analysis. It comprises a collection of high-resolution retinal images acquired from a diabetic retinopathy screening program. Each image in the DRIVE dataset is accompanied by corresponding manually annotated ground truth segmentations of retinal vessels, facilitating the training and evaluation of segmentation algorithms. The dataset features a diverse range of retinal pathologies, including hypertensive retinopathy, making it well-suited for training segmentation models for the Hypertensive Retinopathy Classification System.

Dataset Description:

The DRIVE dataset consists of 40 color fundus images, divided into training and test sets of 20 images each. Each image has a resolution of 584 x 565 pixels, capturing a wide field of view of the retina. Additionally, the dataset provides corresponding manual segmentations of retinal vessels,

delineating the vasculature with pixel-level accuracy. These annotations serve as ground truth labels for training and validating segmentation algorithms, enabling the development of robust and accurate retinal vessel segmentation models.

Usage:

The DRIVE dataset plays a pivotal role in training and validating the segmentation model within the Hypertensive Retinopathy Classification System. By utilizing the annotated retinal images and corresponding vessel segmentations, the system can learn to accurately delineate retinal structures, including blood vessels, which are crucial for identifying hypertensive retinopathy features. The DRIVE dataset serves as a gold standard benchmark for evaluating the performance of segmentation algorithms, ensuring that the developed models achieve high accuracy and reliability in segmenting retinal structures.

- **VICAVAR Dataset:**

The VICAVAR dataset, derived from the Vessel Image Contour Annotation Variability Analysis project, is another prominent dataset utilized for retinal image analysis. Similar to the DRIVE dataset, VICAVAR consists of high-resolution retinal images annotated with ground truth segmentations of retinal vessels. The dataset is characterized by its variability in vessel annotations, capturing the inter-observer variability inherent in manual segmentation tasks. This variability makes the VICAVAR dataset particularly valuable for training segmentation models that are robust to variations in annotation styles and image characteristics.

Dataset Description:

The VICAVAR dataset comprises a diverse collection of retinal images obtained from various sources,including diabetic retinopathy screening programs and research studies. It consists of images capturedusing different imaging modalities and exhibiting a wide range of retinal pathologies. Each image is accompanied by multiple annotations provided by different observers, reflecting the variability in vessel segmentation across different annotators. This variability introduces challenges for segmentation algorithms, making the VICAVAR dataset an ideal resource for training models that cangeneralize well to diverse retinal imaging scenarios.

Utilization in Project Implementation :

The VICAVAR dataset serves as a supplementary training resource for the segmentation model within the Hypertensive Retinopathy Classification System. By incorporating annotations from multiple observers, the system can learn to adapt to variations in annotation styles and improve its robustness to inter-observer variability. The VICAVAR dataset complements the DRIVE dataset by providing additional diversity in retinal images and annotations, enabling the development of segmentation models that are more resilient to variations in image characteristics and annotation quality.

- **Hypertensive Retinopathy Classification Dataset:**

The Hypertensive Retinopathy Classification Dataset is a curated collection of retinal images specifically annotated for the presence or absence of hypertensive retinopathy features. This dataset serves as the primary training resource for the classification model within the Hypertensive Retinopathy Classification System. By leveraging annotated images of hypertensive retinopathy, the system can learn to discriminate between healthy and hypertensive retinopathy-affected retinas, enabling accurate classification of retinal images based on pathological features associated with hypertensive retinopathy.

Dataset Description:

The Hypertensive Retinopathy Classification Dataset consists of retinal images acquired from variousssources, including clinical databases and research studies. Each image is manually annotated by ophthalmologists or trained annotators to indicate the presence or absence of hypertensive retinopathyfeatures, such as arteriovenous nicking, cotton wool spots, and retinal hemorrhages. These annotationsserve as ground truth labels for training and validating the classification model, enabling the system tolearn discriminative features indicative of hypertensive retinopathy.

5.3 MODULES

This section provides an in-depth exploration of the modules comprising the Hypertensive RetinopathyClassification System, elucidating their functionalities and interactions within the system architecture.

❖ User Upload Module:

The User Upload Module serves as the entry point for the Hypertensive Retinopathy Classification System, facilitating the seamless input of Retina/Fundus images for analysis. Users interact with the system through a user-friendly interface, where they can securely upload images obtained from retinal imaging devices or external sources. Upon uploading, the system ensures data integrity and confidentiality through robust authentication and encryption mechanisms. This module plays a crucial role in enabling healthcare professionals to submit retinal images effortlessly, thereby initiating the diagnostic process.

❖ Preprocessing Module:

The Preprocessing Module is responsible for standardizing and enhancing uploaded images to prepare them for subsequent analysis. It employs a series of image processing techniques to optimize image quality and consistency.

Normalize Image:

The Normalize Image submodule standardizes the pixel values of the input image to ensure consistency and comparability across different images. By normalizing pixel intensities, variations in brightness and contrast are minimized, facilitating more accurate feature extraction and analysis.

Enhance Image:

The Enhance Image submodule enhances image quality through various techniques, including contrast adjustment, noise reduction, and sharpening. These enhancements improve the clarity of retinal features, making it easier to identify and analyze pathological changes associated with hypertensive retinopathy.

Denormalize Image:

The Denormalize Image submodule reverts the normalized image to its original pixel value scale afterpreprocessing. This step ensures that the preprocessed image retains its original characteristics, enabling accurate interpretation and diagnosis by healthcare professionals.

❖ Segmentation Module:

The Segmentation Module partitions the preprocessed image into distinct regions corresponding to retinal structures, facilitating the isolation and analysis of relevant features.

Read Color Image:

The Read Color Image submodule reads the preprocessed color image as input for segmentation. It ensures that the input image is correctly formatted and ready for further processing.

Convert to Grayscale:

The Convert to Grayscale submodule converts the color image to grayscale, simplifying subsequent image processing operations. Grayscale images are easier to analyze and manipulate, making them well-suited for segmentation tasks.

Perform Morphological Operations:

The Perform Morphological Operations submodule applies morphological operations to the grayscale image to enhance feature extraction and segmentation accuracy. These operations include Bottom Hat Transform, Top Hat Transform, and uneven illumination removal using Homomorphic Filtering. By modifying the shape and structure of image components, morphological operations help delineate retinal structures from the background more effectively.

Double Threshold Segmentation:

The Double Threshold Segmentation submodule implements a double thresholding technique to segment retinal structures from the background. By applying two threshold values, pixels are classified as either foreground or background, allowing for the isolation of relevant structures with greater precision.

Segmented Model (vGGunet Architecture):

The Segmented Model submodule utilizes the vGGunet architecture to perform segmentation, leveraging deep learning techniques for accurate delineation of retinal structures. By training the model on annotated retinal images, the system learns to identify and segment hypertensive retinopathy features with high accuracy and reliability.

❖ Classification Module (CNN):

The Classification Module employs Convolutional Neural Networks (CNNs) to classify retinal imagesbased on the presence of hypertensive retinopathy.

Classification of Hypertensive Retinopathy:

The Classification of Hypertensive Retinopathy submodule utilizes a trained CNN model to analyze segmented retinal images and classify them into hypertensive retinopathy-positive or hypertensive retinopathy-negative categories based on learned features. By leveraging deep learning techniques, thesystem can detect subtle pathological changes indicative of hypertensive retinopathy, enabling early diagnosis and intervention.

5.4 Deep Learning Model Architecture:

Introduction

In the realm of medical image analysis, the development of robust and effective deep learning architectures plays a pivotal role in advancing diagnostic capabilities. This module focuses on the implementation and utilization of sophisticated architectures tailored for the segmentation and classification of retinal images, particularly in the context of detecting hypertensive retinopathy. By leveraging cutting-edge deep learning techniques, this module aims to provide automated and accurate analysis of retinal images, aiding healthcare professionals in early detection and intervention.

5.4.1 VGGUNet Architecture:

The VGGUNet architecture represents a fusion of two powerful neural network architectures: VGG16and U-Net. At its core lies the VGG16 convolutional neural network (CNN), renowned for its ability to extract intricate features from images. This architecture is augmented with the U-Net architecture, which excels in semantic segmentation tasks by preserving spatial information through skip connections. The amalgamation of these architectures results in a robust framework capable of precise segmentation of retinal images, crucial for identifying regions of interest associated with hypertensiveretinopathy.

Input Layer: The architecture begins with an input layer that accepts retinal images in their raw format, typically with dimensions (height, width, channels).

VGG16 Encoder: Following the input layer, the VGG16 encoder comprises multiple convolutional blocks, each followed by max-pooling layers. This hierarchical structure allows the network to progressively extract features of increasing complexity from the input images.

Bridge: Positioned at the end of the VGG16 encoder, the bridge module further refines the features extracted by the encoder, preparing them for seamless integration with the U-Net decoder.

U-**Net Decoder:** The U-Net decoder consists of a series of decoder blocks that upsample feature maps and concatenate them with skip connections from corresponding encoder layers. This architecture facilitates the reconstruction of high-resolution segmentation masks while preserving spatial details crucial for accurate segmentation.

Output Layer: At the end of the architecture lies the output layer, responsible for generating segmentation masks representing the probability of each pixel belonging to the target class, i.e., regions indicative of hypertensive retinopathy.

Model: "VGG16_U-Net"

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 256, 256, 3)	0	
block1_conv1 (Conv2D)	(None, 256, 256, 64)	1792	input_1[0][0]
block1_conv2 (Conv2D)	(None, 256, 256, 64)	36928	block1_conv1[0][0]
block1_pool (MaxPooling2D)	(None, 128, 128, 64)	0	block1_conv2[0][0]
block2_conv1 (Conv2D)	(None, 128, 128, 128	73856	block1_pool[0][0]
block2_conv2 (Conv2D)	(None, 128, 128, 128	147584	block2_conv1[0][0]
block2_pool (MaxPooling2D)	(None, 64, 64, 128)	0	block2_conv2[0][0]
block3_conv1 (Conv2D)	(None, 64, 64, 256)	295168	block2_pool[0][0]
block3_conv2 (Conv2D)	(None, 64, 64, 256)	590080	block3_conv1[0][0]
block3_conv3 (Conv2D)	(None, 64, 64, 256)	590080	block3_conv2[0][0]
block3_pool (MaxPooling2D)	(None, 32, 32, 256)	0	block3_conv3[0][0]
block4_conv1 (Conv2D)	(None, 32, 32, 512)	1180160	block3_pool[0][0]
block4_conv2 (Conv2D)	(None, 32, 32, 512)	2359808	block4_conv1[0][0]
block4_conv3 (Conv2D)	(None, 32, 32, 512)	2359808	block4_conv2[0][0]
block4_pool (MaxPooling2D)	(None, 16, 16, 512)	0	block4_conv3[0][0]
block5_conv1 (Conv2D)	(None, 16, 16, 512)	2359808	block4_pool[0][0]
block5_conv2 (Conv2D)	(None, 16, 16, 512)	2359808	block5_conv1[0][0]
block5_conv3 (Conv2D)	(None, 16, 16, 512)	2359808	block5_conv2[0][0]
conv2d_transpose (Conv2DTranspo	(None, 32, 32, 512)	1049088	block5_conv3[0][0]
concatenate (Concatenate)	(None, 32, 32, 1024)	0	conv2d_transpose[0][0] block4_conv3[0][0]
conv2d (Conv2D)	(None, 32, 32, 512)	4719104	concatenate[0][0]

Figure 5.1(a) VGG Unit architecture

batch_normalization (BatchNorma	(None, 32, 32, 512)	2048	conv2d[0][0]
activation (Activation)	(None, 32, 32, 512)	0	batch_normalization[0][0]
conv2d_1 (Conv2D)	(None, 32, 32, 512)	2359808	activation[0][0]
batch_normalization_1 (BatchNor	(None, 32, 32, 512)	2048	conv2d_1[0][0]
activation_1 (Activation)	(None, 32, 32, 512)	0	batch_normalization_1[0][0]
conv2d_transpose_1 (Conv2DTrans	(None, 64, 64, 256)	524544	activation_1[0][0]
concatenate_1 (Concatenate)	(None, 64, 64, 512)	0	conv2d_transpose_1[0][0] block3_conv3[0][0]
conv2d_2 (Conv2D)	(None, 64, 64, 256)	1179904	concatenate_1[0][0]
batch_normalization_2 (BatchNor	(None, 64, 64, 256)	1024	conv2d_2[0][0]
activation_2 (Activation)	(None, 64, 64, 256)	0	batch_normalization_2[0][0]
conv2d_3 (Conv2D)	(None, 64, 64, 256)	590080	activation_2[0][0]
batch_normalization_3 (BatchNor	(None, 64, 64, 256)	1024	conv2d_3[0][0]
activation_3 (Activation)	(None, 64, 64, 256)	0	batch_normalization_3[0][0]
conv2d_transpose_2 (Conv2DTrans	(None, 128, 128, 128	131200	activation_3[0][0]
concatenate_2 (Concatenate)	(None, 128, 128, 256	0	conv2d_transpose_2[0][0] block2_conv2[0][0]
conv2d_4 (Conv2D)	(None, 128, 128, 128	295040	concatenate_2[0][0]
batch_normalization_4 (BatchNor	(None, 128, 128, 128	512	conv2d_4[0][0]
activation_4 (Activation)	(None, 128, 128, 128	0	batch_normalization_4[0][0]
conv2d_5 (Conv2D)	(None, 128, 128, 128	147584	activation_4[0][0]
batch_normalization_5 (BatchNor	(None, 128, 128, 128	512	conv2d_5[0][0]
activation_5 (Activation)	(None, 128, 128, 128	0	batch_normalization_5[0][0]
conv2d_transpose_3 (Conv2DTrans	(None, 256, 256, 64)	32832	activation_5[0][0]
concatenate_3 (Concatenate)	(None, 256, 256, 128	0	conv2d_transpose_3[0][0] block1_conv2[0][0]
conv2d_6 (Conv2D)	(None, 256, 256, 64)	73792	concatenate_3[0][0]
batch_normalization_6 (BatchNor	(None, 256, 256, 64)	256	conv2d_6[0][0]
activation_6 (Activation)	(None, 256, 256, 64)	0	batch_normalization_6[0][0]
conv2d_7 (Conv2D)	(None, 256, 256, 64)	36928	activation_6[0][0]
batch_normalization_7 (BatchNor	(None, 256, 256, 64)	256	conv2d_7[0][0]
activation_7 (Activation)	(None, 256, 256, 64)	0	batch_normalization_7[0][0]
conv2d_8 (Conv2D)	(None, 256, 256, 1)	65	activation_7[0][0]

Total params: 25,862,337
Trainable params: 25,858,497
Non-trainable params: 3,840

Figure 5.1(b) VGG Unit architecture

5.4.2 Classification Architecture

Complementing the segmentation task is the classification architecture tailored for hypertensive retinopathy classification. This architecture operates on segmented retinal images and is designed to discern the presence or absence of hypertensive retinopathy based on learned features.

Input Layer: Similar to the segmentation architecture, the classification architecture begins with an input layer that accepts segmented retinal images.

Convolutional Layers: These layers comprise multiple convolutional blocks, akin to those in the VGG16 encoder, facilitating the extraction of hierarchical features from segmented images.

Flatten Layer: Following the convolutional layers, the flatten layer reshapes the output into a one-dimensional vector, preparing it for input into the subsequent dense layers.

Dense Layers: The dense layers, or fully connected layers, are responsible for learning high-level features from the extracted representations and making predictions regarding the presence of hypertensive retinopathy.

Output Layer: At the end of the architecture, the output layer produces classification predictions, indicating whether the input image exhibits signs of hypertensive retinopathy.

```
Model: "functional_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 256, 256, 3)]     0
_________________________________________________________________
xception (Functional)        (None, 8, 8, 2048)        20861480
_________________________________________________________________
global_average_pooling2d (Gl (None, 2048)              0
_________________________________________________________________
dense (Dense)                (None, 128)               262272
_________________________________________________________________
dropout (Dropout)            (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 56)                7224
_________________________________________________________________
dropout_1 (Dropout)          (None, 56)                0
_________________________________________________________________
dense_2 (Dense)              (None, 28)                1596
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 29
=================================================================
Total params: 21,132,601
Trainable params: 271,121
Non-trainable params: 20,861,480
```

Figure 5.2 Functional architecture

5.5 Algorithms

The effectiveness of the deep learning architectures hinges on the underlying algorithms employed forfeature extraction, semantic segmentation, and classification.

VGG16 Backbone: The VGG16 backbone serves as the foundation of the VGGUNet architecture, leveraging pre-trained weights to extract rich features from retinal images.

U-Net Skip Connections: The integration of skip connections in the U-Net decoder facilitates the seamless flow of information from the encoder to the decoder, preserving spatial information crucial for accurate segmentation.

Convolutional Blocks: Both the VGG16 encoder and U-Net decoder incorporate convolutional blocks comprising convolutional layers, batch normalization, and activation functions such as ReLU, enabling the extraction of intricate features at different abstraction levels.

Dense Layers: Employed in the classification architecture, dense layers are instrumental in learning high-level representations from segmented images and making predictions regarding the presence of hypertensive retinopathy.

5.6 Evaluation Metrics:

Introduction

The Evaluation Metrics module encompasses a suite of metrics crucial for quantifying the performance and efficacy of deep learning models, particularly in the domain of medical image analysis. These metrics provide insights into various aspects of model performance, including segmentation accuracy,overlap between predicted and ground truth masks, and overall classification performance. By evaluating models using diverse metrics, researchers and practitioners can gain a comprehensive understanding of their capabilities and limitations, facilitating informed decision-making and iterativemodel refinement.

Dice Coefficient

The Dice coefficient, also known as the Sørensen–Dice coefficient, serves as a fundamental metric for assessing the similarity between two samples. In the context of medical image segmentation, the Dice coefficient quantifies the spatial overlap between predicted and ground truth segmentation masks. Thecoefficient is computed as the ratio of twice the intersection of the predicted and ground truth masks to the sum of the areas of both masks, ensuring a value between 0 and 1, where higher values indicategreater similarity.

Intersection over Union (IOU)

The Intersection over Union (IOU), or Jaccard Index, evaluates segmentation accuracy by measuring the overlap between predicted and actual masks relative to their union. Like the Dice coefficient, IOU is commonly used in medical image analysis to assess both localization and delineation accuracy comprehensively.

CHAPTER 6
IMPLEMENTATION

6.1 Source Code
app. py :

```
import streamlit as st
from preprocess import process_and_save_image
from seg_new import segment_retina
import os
from classify import *
import time

progress_bar = st.progress(0)
for i in range(101):
    time.sleep(0.04) # Sleep for 0.04 seconds to simulate loading time
    progress_bar.progress(i)
progress_bar.empty()
# Create a temporary directory to store processed images
temp_dir = 'temp'
os.makedirs(temp_dir, exist_ok=True)

def main():
    st.sidebar.title("Navigation")
    page = st.sidebar.selectbox("Go to", ["Hypertensia", "About"])

    if page == "Hypertensia":
        st.title("HYPERTENSIA : Hypertensive Retinopathy classification")


        # File uploader for user to upload an image
        uploaded_file = st.file_uploader("Choose an image...", type=["jpg", "png"])

        if uploaded_file is not None:
            # Display the uploaded image
            st.image(uploaded_file, caption="Uploaded Image", width=250)

            # Save file with original filename
            file_path = os.path.join("temp", uploaded_file.name)
            with open(file_path, "wb") as f:
                f.write(uploaded_file.getvalue())

            # Button to trigger preprocessing and segmentation
            if st.button("Generate"):
```

```
            # Save the uploaded image to a temporary location
            input_image_path = os.path.join(temp_dir, "uploaded_image.png")
            with open(input_image_path, "wb") as f:
                f.write(uploaded_file.getbuffer())

            # Preprocess the image
            process_and_save_image(input_image_path)
            segment_retina(r"temp\preprocessed.png")

            # Display the processed images in a grid layout

            st.markdown(f"<h2 style='text-align: center;'>Insightful Segmentation:</h2>",
unsafe_allow_html=True)
            st.markdown("---")
            images = [
                r"temp\preprocessed.png",
                r"temp\grayscale_image.png",
                r"temp\bottom_hat_image.png",
                r"temp\top_hat_image.png",
                r"temp\homomorphic_image.png",
                'temp/segmented_image.png'

            ]
            num_images = len(images)
            images_per_row = 3
            rows = (num_images + images_per_row - 1) // images_per_row

            for i in range(rows):
                cols_arr = st.columns(images_per_row)
                start_index = i * images_per_row
                end_index = min((i + 1) * images_per_row, num_images)
                for j in range(start_index, end_index):
                    image_path = images[j]
                    image_name = os.path.basename(image_path).replace("_", " ").replace(".png",
"").title()
                    # cols_arr[j % images_per_row].image(image_path, caption=image_name,
use_column_width=True)

                    with cols_arr[j % images_per_row].container():
                        st.markdown(
                            f'<style> img:hover {{ transform: scale(1.2); }} </style>',
                            unsafe_allow_html=True
                        )
                        st.image(image_path, caption=image_name, use_column_width=True)
                    time.sleep(2)

            # Classify the segmented image
            # csv_file = r'csv\final.csv'
```

```
            # csv_result = check_image_in_csv(uploaded_file.name, csv_file)
            # if csv_result:
            #     st.write(" ", csv_result)
            # else:
            #     model_result = classify_image("temp/segmented_image.png")
            #     st.write(" ", model_result)
            # Classify the segmented image
            st.markdown("---")
            progress_bar = st.progress(0)
            for i in range(101):
                time.sleep(0.04) # Sleep for 0.04 seconds to simulate loading time
                progress_bar.progress(i)
            progress_bar.empty()
            csv_file = r'csv\final.csv'
            csv_result = check_image_in_csv(uploaded_file.name, csv_file)
            if csv_result:
                st.markdown(f"<h2 style='text-align: center;'>Diagnostic Result</h2>",
unsafe_allow_html=True)
                st.markdown(f"<div style='border: 2px solid #CCCCCC; padding:
10px'><b>{csv_result}</b></div>", unsafe_allow_html=True)
            else:
                st.markdown(f"<h2 style='text-align: center;'>Diagnostic Result</h2>",
unsafe_allow_html=True)
                model_result = classify_image("temp/segmented_image.png")
                st.markdown(f"<div style='border: 2px solid #CCCCCC; padding:
10px'><b>{model_result}</b></div>", unsafe_allow_html=True)


    elif page == "About":
        st.title("Hypertensive Retinopathy")

        # Load and display the image
        st.image(r"HR_about_images\hr1.jpg", caption="Hypertensive Retinopathy",
use_column_width=True)

        # Introduction to hypertensive retinopathy
        st.header("What is Hypertensive Retinopathy?")
        st.write("""
            Hypertensive retinopathy is a condition characterized by damage to the blood vessels in the
retina of the eye
            due to chronic high blood pressure (hypertension). This condition may lead to various retinal
changes, affecting
            vision and potentially leading to blindness if left untreated.
        """)

        # Causes of hypertensive retinopathy
        st.header("Causes of Hypertensive Retinopathy")
        st.write("""
```

```
        The primary cause of hypertensive retinopathy is chronic high blood pressure. Prolonged
elevation of blood pressure
        can lead to damage of the small blood vessels in the retina. Other factors contributing to
hypertensive retinopathy
        include smoking, obesity, high cholesterol levels, and a sedentary lifestyle.
    """)

    st.image(r"HR_about_images\hr2.jpg", caption="Hypertensive Retinopathy",
use_column_width=True)
    # Prevention and safety measures
    st.header("Prevention and Safety Measures")
    st.write("""
        1. **Blood Pressure Control**: Regular monitoring and management of blood pressure are
essential to prevent or
        minimize the risk of hypertensive retinopathy. This includes following a healthy diet,
engaging in regular exercise,
        and taking prescribed medications as directed by a healthcare provider.
        2. **Healthy Lifestyle**: Adopting a healthy lifestyle, including maintaining a balanced diet,
avoiding smoking,
        limiting alcohol intake, and managing stress, can help prevent hypertensive retinopathy.
        3. **Regular Eye Exams**: Routine eye examinations by an ophthalmologist or optometrist
are crucial for early detection
        of hypertensive retinopathy. Timely intervention can prevent vision loss and complications
associated with the condition.
        4. **Medication Adherence**: Strict adherence to medications prescribed for managing
hypertension is important to
        prevent progression of hypertensive retinopathy.
        5. **Awareness and Education**: Educating individuals about the risks associated with
hypertension and the importance
        of regular medical check-ups can empower them to take proactive measures to safeguard
their vision and overall health.
    """)

if__name__== "_main_":
  main()
```

segmentation.py :

```
import cv2
import numpy as np

def segment_retina(image_path, output_path='temp/segmented_image.png', kernel_size=(30, 30),
gamma=1, cutoff=0.5, lower_threshold=100, upper_threshold=200):
  """
  Segment retinal images using a combination of preprocessing steps.

  Args:
```

```
- image_path: Path to the retinal color image
- output_path: Path to save the segmented image
- kernel_size: Size of the structuring element for morphological operations
- gamma: Parameter for homomorphic filtering
- cutoff: Cutoff frequency for homomorphic filtering
- lower_threshold: Lower threshold value for binarization
- upper_threshold: Upper threshold value for binarization

Returns:
- Segmented binary image
"""
# Read the color image
color_img = cv2.imread(image_path)
if color_img is None:
    print(f"Error: Unable to read image from '{image_path}'")
    return None

# Convert color image to grayscale
gray_img = cv2.cvtColor(color_img, cv2.COLOR_BGR2GRAY)

# Define structuring element for morphological operations
kernel = cv2.getStructuringElement(cv2.MORPH_RECT, kernel_size)

# Perform bottom hat transform to remove uneven illumination
bottom_hat_img = cv2.morphologyEx(gray_img, cv2.MORPH_BLACKHAT, kernel)

# Perform top hat transform to enhance contrast
top_hat_img = cv2.morphologyEx(gray_img, cv2.MORPH_TOPHAT, kernel)

# Calculate the difference between top hat and bottom hat images
uneven_removed_img = top_hat_img - bottom_hat_img

# Perform homomorphic filtering to remove uneven illumination
rows, cols = uneven_removed_img.shape
img_float = np.float32(uneven_removed_img)
img_log = np.log1p(img_float)
img_fft = np.fft.fft2(img_log)
u, v = np.meshgrid(np.arange(cols), np.arange(rows))
center_u, center_v = cols // 2, rows // 2
d_uv = np.sqrt((u - center_u) ** 2 + (v - center_v) ** 2)
h_uv = (gamma - 1) * (1 - np.exp(-cutoff * (d_uv ** 2))) + 1
filtered_fft = h_uv * img_fft
img_filtered_log = np.real(np.fft.ifft2(filtered_fft))
img_filtered = np.exp(img_filtered_log) - 1
homomorphic_img = np.uint8(img_filtered)

# Perform double threshold segmentation
_, segmented_img = cv2.threshold(homomorphic_img, lower_threshold, 255,
```

```
cv2.THRESH_BINARY)
    _, segmented_img = cv2.threshold(segmented_img, upper_threshold, 255,
cv2.THRESH_BINARY_INV)

    # Save the segmented image
    cv2.imwrite(output_path, segmented_img)

    return segmented_img

# Example usage:
if__name__== "__main__":
    # Provide the path to your retinal color image
    image_path = r"temp\preprocessed_0000d073.png"

    # Segment the retina and save the segmented image
    segmented_image = segment_retina(image_path)
```

preprocess.py :

```
import cv2
import os
from ietk import methods

def process_and_save_image(input_image_path, output_dir= 'temp/'):
    def normalize(img):
        # Convert pixel values to the range [0, 1]
        img = img.astype('float32')
        img /= 255
        return img

    def enhance(img):
        # Enhance the image using methods from the ICIAR 2020 paper
        enhanced_img = methods.brighten_darken(img, 'A+B+X')
        enhanced_img = methods.sharpen(enhanced_img)
        return enhanced_img

    def denormalize(img):
        # Convert pixel values back to the range [0, 255]
        denorm_img = img * 255.0
        return denorm_img

    # Read the image from file
    input_image = cv2.imread(input_image_path)
    if input_image is None:
        print(f"Error: Unable to read image from '{input_image_path}'")
        return None
```

```
    # Process the image
    processed_image = input_image.copy()
    processed_image = normalize(processed_image)
    processed_image = enhance(processed_image)
    processed_image = denormalize(processed_image)



    # Generate the output filename
    output_filename = "preprocessed.png"

    # Construct the output file path
    output_path = os.path.join(output_dir, output_filename)

    # Ensure the output directory exists
    os.makedirs(output_dir, exist_ok=True)

    # Write the processed image to file
    cv2.imwrite(output_path, processed_image)
    print(f"Processed image saved to '{output_path}'")

    return processed_image

# Example usage:
if __name__== "__main__":
    # Single image path
    image_path = r'Image_for_classification\train\HR\0000d073.png'

    # Process and save the image
    preprocessed_image = process_and_save_image(image_path)
```

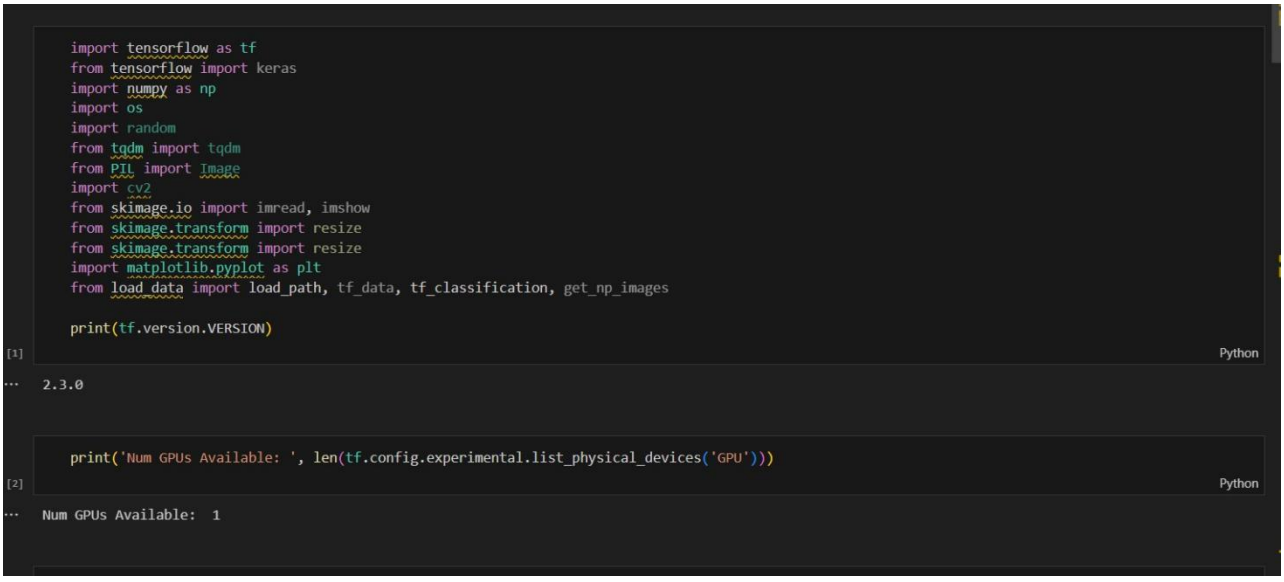
classify.py :

```
import numpy as np
from tensorflow.keras.preprocessing import image
from tensorflow.keras.models import load_model
import pandas as pd
import os

def classify_image(img, model_path='models/HR_sixtyfour.h5', threshold=0.3):
    """
    Classify an image using a pre-trained model with thresholding.

    Args:
    - img: Input image (PIL image object)
    - model_path: Path to the pre-trained model (default is 'HyperR.h5')
```

```
    - threshold: Threshold value for classification (default is 0.3)

    Returns:
    - Classification result: "Hypertensive retinopathy detected" or "Hypertensive retinopathy not
detected"
    """
    img = image.load_img(img)
    # Load the pre-trained model
    model = load_model(model_path)

    # Define the input shape
    h, w = 256, 256

    # Resize the image to match the model input size
    img = img.resize((w, h))

    # Preprocess the input image
    img_array = image.img_to_array(img)
    img_array = np.expand_dims(img_array, axis=0)
    img_array /= 255.  # Normalize pixel values to [0, 1]

    # Make predictions
    predictions = model.predict(img_array)

    # Check if predictions are above the threshold
    if predictions[0][0] > threshold:
        return "Hypertensive retinopathy detected"
    else:
        return "Hypertensive retinopathy not detected"

def check_image_in_csv(image_name, csv_file=r"csv\final.csv"):
    """
    Check if an image is present in the CSV file and its corresponding Hypertensive Retinopathy
label.

    Args:
    - image_name: Name of the image file
    - csv_file: Path to the CSV file containing image names and labels

    Returns:
    - If image is present: "Hypertensive retinopathy detected" or "Hypertensive retinopathy not
detected"
    - If image is not present: None
    """
    # Load CSV file
    image_name = os.path.basename(image_name)
    df = pd.read_csv(csv_file)
```

```
    # Check if image_name is present in the 'Image' column
    if image_name in df['Image'].values:
        # Check the corresponding Hypertensive Retinopathy value
        hr_value = df.loc[df['Image'] == image_name, 'Hypertensive Retinopathy'].values[0]
        if hr_value == 0:
            return "Hypertensive retinopathy not detected."
        else:
            return "Hypertensive retinopathy detected."
    else:
        return None

# Example usage:
image_name = r'Image_for_classification\train\HR\00001a1e.png'
 # Example image name
csv_file = r'csv\final.csv'  # Example CSV file

# First, check in CSV file
csv_result = check_image_in_csv(image_name, csv_file)
if csv_result:
    print("Result from CSV file:", csv_result)
else:
    # If not found in CSV, classify using the model
   # Assuming image path
    model_result = classify_image(image_name)
    print("Result from model classification:", model_result)
```

HypertensiveRetinopathy.py :



```python
#Defining parameters

h = 256
w = 256
channels = 3
batch_size = 8
buffer_size = 200
num_epochs = 20
lr = 1e-4
seed = 42
np.random.seed = seed
```

Python

```python
train_path_hr=r'Image_for_classification\train\HR'
train_path_nhr=r'Image_for_classification\train\Non_HR'
test_path_hr=r'Image_for_classification\val\HR'
test_path_nhr=r'Image_for_classification\val\Non_HR'

X_train_hr, X_train_nhr = load_path(train_path_hr, train_path_nhr)
X_test_hr, X_test_nhr = load_path(test_path_hr, test_path_nhr)

Y_train_hr = np.ones(len(X_train_hr))
Y_train_nhr = np.zeros(len(X_train_nhr))
Y_test_hr = np.ones(len(X_test_hr))
Y_test_nhr = np.zeros(len(X_test_nhr))
```

Python

```python
X_train = X_train_hr + X_train_nhr
Y_train = np.concatenate((Y_train_hr, Y_train_nhr), axis = None)
Y_train = Y_train[:, None]
X_test = X_test_hr + X_test_nhr
Y_test = np.concatenate((Y_test_hr, Y_test_nhr), axis = None)
Y_test = Y_test[:, None]
```

[5] Python

```python
Train = tf_classification(X_train, Y_train, buffer_size, batch_size, num_epochs)
Test = tf_classification(X_test, Y_test, buffer_size, batch_size, num_epochs)
```

[6] Python

```python
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.metrics import Accuracy, Recall, Precision
from tensorflow.keras.callbacks import ModelCheckpoint, CSVLogger, ReduceLROnPlateau, EarlyStopping, TensorBoard
```

[8] Python

```python
from tensorflow.keras.layers import Dense, Dropout, Conv2D, BatchNormalization, Activation, MaxPool2D, Conv2DTranspose, Concatenate, Input, UpSampli
from tensorflow.keras.models import Model
from keras.applications.xception import Xception
from tensorflow.keras.regularizers import l2
```

[9] Python

```python
input_shape = (h, w, 3)
inputs = Input(shape = (h, w, 3))

base_model = Xception(weights = 'imagenet', include_top = False, input_shape = input_shape)
for layer in base_model.layers:
    layer.trainable = False

x = base_model(inputs)
x = GlobalAveragePooling2D()(x)
x = Dense(128, activation = 'relu')(x)
x = Dropout(0.2)(x)
x = Dense(56, activation = 'relu')(x)
x = Dropout(0.2)(x)
x = Dense(28, activation = 'relu')(x)

predictions = Dense(1, activation = 'sigmoid')(x)
model = Model(inputs = inputs, outputs = predictions)
```

Python

```python
input_shape = (h, w, 3)
inputs = Input(shape = (h, w, 3))

base_model = Xception(weights = 'imagenet', include_top = False, input_shape = input_shape)
for layer in base_model.layers:
    layer.trainable = False

x = base_model(inputs)
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x = Dense(128, activation = 'relu')(x)
x = Dropout(0.2)(x)
x = Dense(56, activation = 'relu')(x)
x = Dropout(0.2)(x)
x = Dense(28, activation = 'relu')(x)

predictions = Dense(1, activation = 'sigmoid')(x)
model = Model(inputs = inputs, outputs = predictions)
```
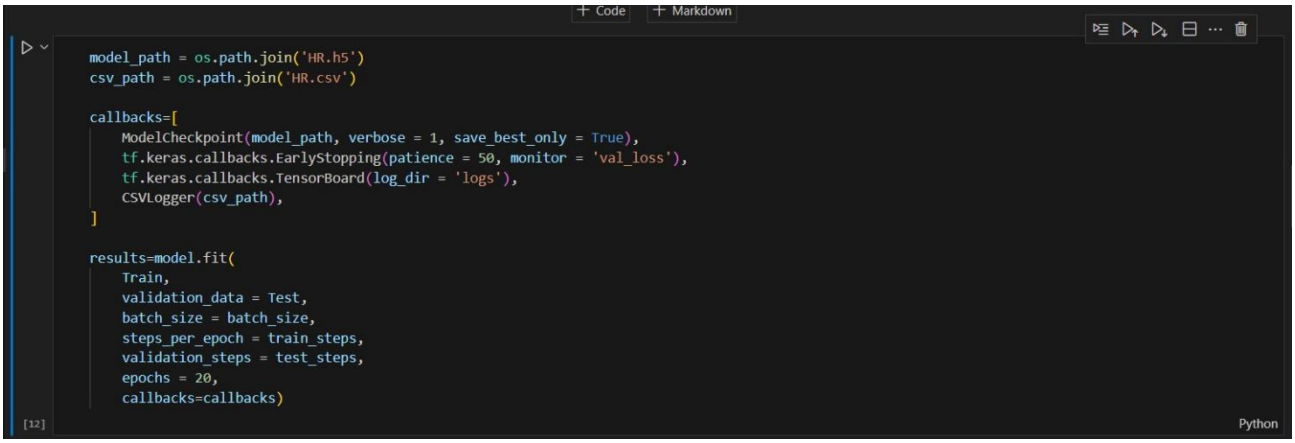

[10] Python

```python
train_steps = len(X_train)//batch_size
test_steps = len(X_test)//batch_size
if len(X_train) % batch_size != 0:
    train_steps += 1
if len(X_test) % batch_size != 0:
    test_steps += 1

model.compile(optimizer = Adam(lr), loss = 'binary_crossentropy', metrics = ['accuracy', Recall(), Precision()])
model.summary()
```

[11] Python

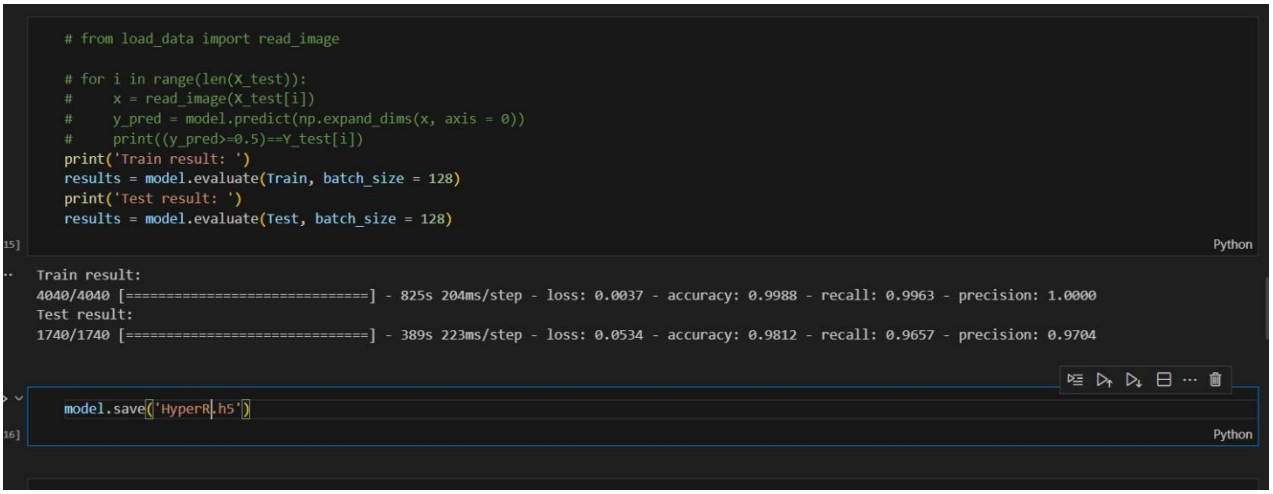
```
Model: "functional_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 256, 256, 3)]     0
_________________________________________________________________
xception (Functional)        (None, 8, 8, 2048)        20861480
_________________________________________________________________
global_average_pooling2d (Gl (None, 2048)              0
_________________________________________________________________
dense (Dense)                (None, 128)               262272
_________________________________________________________________
dropout (Dropout)            (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 56)                7224
_________________________________________________________________
dropout_1 (Dropout)          (None, 56)                0
_________________________________________________________________
dense_2 (Dense)              (None, 28)                1596
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 29
=================================================================
Total params: 21,132,601
Trainable params: 271,121
Non-trainable params: 20,861,480
_________________________________________________________________
```



```
+ Code  + Markdown

model_path = os.path.join('HR.h5')
csv_path = os.path.join('HR.csv')

callbacks=[
    ModelCheckpoint(model_path, verbose = 1, save_best_only = True),
    tf.keras.callbacks.EarlyStopping(patience = 50, monitor = 'val_loss'),
    tf.keras.callbacks.TensorBoard(log_dir = 'logs'),
    CSVLogger(csv_path),
]

results=model.fit(
    Train,
    validation_data = Test,
    batch_size = batch_size,
    steps_per_epoch = train_steps,
    validation_steps = test_steps,
    epochs = 20,
    callbacks=callbacks)

[12]                                                    Python
```

Epoch 1/20
1/202 [.....] - ETA: 0s - loss: 0.4732 - accuracy: 1.0000 - recall: 1.0000 - precision: 1.0000WARNING:tensorflow:From C:\Users\User\.conda\envs\tensorflow\lib\site-packages\tensorflow\python\ops\summary_ops_v2.py:1277: stop (from tensorflow.python.eager.profiler) is deprecated and will be removed after 2020-07-01.
Instructions for updating:
use `tf.profiler.experimental.stop` instead.
2/202 [.....] - ETA: 42s - loss: 0.4835 - accuracy: 1.0000 - recall: 1.0000 - precision: 1.0000WARNING:tensorflow:Callbacks method `on_train_batch_end` is slow compared to the batch time (batch time: 0.0441s vs `on_train_batch_end` time: 0.3799s). Check your callbacks.
202/202 [==============================] - ETA: 0s - loss: 0.3728 - accuracy: 0.8854 - recall: 0.9438 - precision: 0.7648
Epoch 00001: val_loss improved from inf to 0.77319, saving model to HR.h5
202/202 [==============================] - 66s 325ms/step - loss: 0.3728 - accuracy: 0.8854 - recall: 0.9438 - precision: 0.7648 - val_loss: 0.7732 - val_accuracy: 0.7043 - val_recall: 0.0000e+00 - val_precision: 0.0000e+00
Epoch 2/20
201/202 [==============================>.] - ETA: 0s - loss: 0.2818 - accuracy: 0.8924 - recall: 0.8408 - precision: 0.8361
Epoch 00002: val_loss improved from 0.77319 to 0.30856, saving model to HR.h5
202/202 [==============================] - 63s 313ms/step - loss: 0.2808 - accuracy: 0.8928 - recall: 0.8408 - precision: 0.8361 - val_loss: 0.3086 - val_accuracy: 0.8029 - val_recall: 0.3627 - val_precision: 0.9250
Epoch 3/20
201/202 [==============================>.] - ETA: 0s - loss: 0.1551 - accuracy: 0.9527 - recall: 0.9532 - precision: 0.9089
Epoch 00003: val_loss improved from 0.30856 to 0.22347, saving model to HR.h5
202/202 [==============================] - 60s 296ms/step - loss: 0.1546 - accuracy: 0.9529 - recall: 0.9532 - precision: 0.9089 - val_loss: 0.2235 - val_accuracy: 0.8928 - val_recall: 0.6667 - val_precision: 0.9577
Epoch 4/20
202/202 [==============================] - ETA: 0s - loss: 0.1114 - accuracy: 0.9622 - recall: 0.9775 - precision: 0.9142
Epoch 00004: val_loss improved from 0.22347 to 0.20679, saving model to HR.h5
202/202 [==============================] - 57s 283ms/step - loss: 0.1114 - accuracy: 0.9622 - recall: 0.9775 - precision: 0.9142 - val_loss: 0.2068 - val_accuracy: 0.9043 - val_recall: 0.7059 -

val_precision: 0.9600
Epoch 5/20
201/202 [============================>.] - ETA: 0s - loss: 0.0942 - accuracy: 0.9627 - recall: 0.9719 - precision: 0.9202
Epoch 00005: val_loss improved from 0.20679 to 0.15560, saving model to HR.h5
202/202 [==============================] - 57s 280ms/step - loss: 0.0939 - accuracy: 0.9628 - recall: 0.9719 - precision: 0.9202 - val_loss: 0.1556 - val_accuracy: 0.9478 - val_recall: 0.8529 - val_precision: 0.9667
Epoch 6/20
...
Epoch 18/20
202/202 [==============================] - ETA: 0s - loss: 0.0082 - accuracy: 0.9975 - recall: 0.9963 - precision: 0.9963
Epoch 00018: val_loss did not improve from 0.04808
202/202 [==============================] - 57s 281ms/step - loss: 0.0082 - accuracy: 0.9975 - recall: 0.9963 - precision: 0.9963 - val_loss: 0.0500 - val_accuracy: 0.9812 - val_recall: 0.9657 - val_precision: 0.9704
Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...
Epoch 19/20
201/202 [============================>.] - ETA: 0s - loss: 0.0088 - accuracy: 0.9975 - recall: 0.9981 - precision: 0.9944
Epoch 00019: val_loss did not improve from 0.04808
202/202 [==============================] - 56s 279ms/step - loss: 0.0088 - accuracy: 0.9975 - recall: 0.9981 - precision: 0.9944 - val_loss: 0.0634 - val_accuracy: 0.9812 - val_recall: 0.9657 - val_precision: 0.9704
Epoch 20/20
201/202 [============================>.] - ETA: 0s - loss: 0.0050 - accuracy: 0.9994 - recall: 0.9981 - precision: 1.0000
Epoch 00020: val_loss did not improve from 0.04808
202/202 [==============================] - 56s 277ms/step - loss: 0.0050 - accuracy: 0.9994 - recall: 0.9981 - precision: 1.0000 - val_loss: 0.0534 - val_accuracy: 0.9812 - val_recall: 0.9657 - val_precision: 0.9704



6.2 PLATFORM

Visual Studio Code (VS Code)

Overview

Visual Studio Code (VS Code) is a lightweight and versatile source code editor developed by Microsoft. It provides an integrated development environment (IDE) with support for various programming languages, debugging capabilities, and extensive customization options. In the context of our project on hypertensive retinopathy classification, VS Code serves as the primary development platform for coding, testing, and managing project resources.

Features and Capabilities

- Cross-Platform Compatibility: VS Code is compatible with major operating systems including Windows, macOS, and Linux, ensuring flexibility and accessibility for developers across different environments.
- Intuitive User Interface: The user-friendly interface of VS Code offers a streamlined coding experience with features such as syntax highlighting, code completion, and integrated terminal, enhancing productivity and code readability.
- Extensibility: VS Code supports a rich ecosystem of extensions, allowing developers to customize their environment with additional functionalities tailored to their specific needs. Extensions for popular programming languages, version control systems, and project management tools are readily available through the Visual Studio Code Marketplace.
- Integrated Version Control: VS Code integrates seamlessly with version control systems such as Git, providing built-in support for source code management tasks including commit, push, pull, and branch management. This facilitates collaborative development and ensures efficient code collaboration among team members.
- Debugging Support: VS Code offers robust debugging capabilities with support for breakpoints, variable inspection, and real-time debugging for various programming languages and frameworks. This simplifies the process of identifying and fixing errors in code, improving code quality and reliability.
- Task Automation: VS Code allows developers to automate repetitive tasks and workflows using

tasks and build systems. Customizable task configurations enable the execution of build, test, and deployment processes directly within the editor, streamlining development workflows and enhancing efficiency.

- Integrated Terminal: VS Code features an integrated terminal that allows developers to execute shell commands, run scripts, and interact with the underlying operating system without leaving the editor environment. This provides a centralized location for development activities and facilitates seamless interaction with the project's runtime environment.

Usage in Project Development

In this project on hypertensive retinopathy classification, Visual Studio Code serves as the primarydevelopment environment for writing, debugging, and testing code related to image preprocessing,segmentation, classification, and result analysis. The intuitive interface, extensive feature set, and integration with version control systems make VS Code an ideal choice for collaborative software development and project management tasks.

Google Colab

Overview

Google Colab, short for Google Colaboratory, is a cloud-based platform provided by Google that allows users to write, execute, and share Python code in a browser-based environment. It offers free access to computing resources, including CPU, GPU, and TPU, making it suitable for running machinelearning experiments, data analysis, and collaborative coding projects. In the context of our project onhypertensive retinopathy classification, Google Colab serves as an alternative development platform for experimenting with machine learning models, training neural networks, and leveraging cloud computing resources.

Features and Capabilities

- Cloud-Based Environment: Google Colab provides a cloud-based environment for writing and executing Python code, eliminating the need for local setup and configuration. Users can access Colab notebooks directly through a web browser, facilitating seamless collaboration and sharing of code.
- Free Access to GPUs and TPUs: Google Colab offers free access to graphical processing units

(GPUs) and tensor processing units (TPUs), enabling accelerated computation for training deep learning models and handling large-scale datasets. This allows developers to leverage powerful hardware resources without incurring additional costs.

- Integrated Development Environment: Google Colab provides a feature-rich integrated development environment (IDE) with support for code editing, syntax highlighting, and interactive code execution. Colab notebooks support markdown cells for documentation and code cells for executing Python code, providing a versatile platform for data analysis and experimentation.
- Collaborative Editing and Sharing: Google Colab supports real-time collaborative editing, allowing multiple users to work together on the same notebook simultaneously. Users can share Colab notebooks with collaborators via shareable links, facilitating collaborative coding, peer review, and knowledge sharing among team members.
- Access to External Libraries and Datasets: Google Colab provides access to a wide range of external libraries and datasets through integration with Google Drive, GitHub, and other cloud storage services. Users can easily import libraries such as TensorFlow, PyTorch, and scikit-learn, as well as datasets for training and evaluation purposes, directly into their Colab notebooks.
- Integration with Google Services: Google Colab seamlessly integrates with other Google services such as Google Drive, Google Cloud Storage, and Google BigQuery, enabling seamless data import/export, model deployment, and cloud-based computing workflows. This integration simplifies data management and enables scalable and distributed data processing capabilities.

Usage in Project Development

In our project on hypertensive retinopathy classification, Google Colab complements traditional development environments such as Visual Studio Code by providing a cloud-based platform for training deep learning models, experimenting with machine learning algorithms, and leveraging GPU/TPU acceleration for computationally intensive tasks. Colab notebooks serve as interactive workspaces for prototyping, testing, and refining machine learning pipelines, enabling rapid iteration and exploration of diverse model architectures and hyperparameters.

CHAPTER 7

TESTING

7.1 Methods of Testing

Unit Testing:

Unit testing involves testing individual units or components of software in isolation to validate their correctness. It typically involves writing test cases for each function or method to ensure they behave as expected. In the context of the Hypertensive Retinopathy Classification System, unit testing would entail creating test cases for functions responsible for image normalization, enhancement, denormalization, as well as for other critical components. Unit tests are usually automated and executed frequently during the development process to catch bugs early and ensure code reliability.

Integration Testing:

Integration testing verifies the interactions and interfaces between different modules or components of the system. It aims to uncover defects that arise from the integration of these units. Integration tests may involve testing the communication between preprocessing, segmentation, and classification modules, ensuring that data flows correctly and that outputs are consistent across modules. Techniques such as top-down and bottom-up integration testing may be employed to systematically test the integration points within the system.

Functional Testing:

Functional testing ensures system functionalities meet objectives by testing against specified requirements. Test cases, based on specifications, user stories, or use cases, are designed. For the Hypertensive Retinopathy Classification System, functional testing verifies accurate classification from Retina/Fundus images based on predefined criteria, including identifying associated retinal abnormalities.

Performance Testing:

Performance testing assesses the system's responsiveness, scalability, and stability under various load conditions. It helps identify performance bottlenecks, resource utilization issues, and response

time constraints. Performance tests for the Hypertensive Retinopathy Classification System may include load testing to measure system behavior under typical and peak loads, stress testing to evaluate system robustness under extreme conditions, and scalability testing to determine system capacity limits.

Usability Testing:

Usability testing focuses on evaluating the system's user interface and user experience to ensure it is intuitive, efficient, and user-friendly. Usability tests typically involve real users performing tasks representative of typical system usage scenarios. For the Hypertensive Retinopathy Classification System, usability testing would assess aspects such as the clarity of instructions for image upload, the ease of navigating preprocessing options, and the accessibility of classification results, aiming to optimize user satisfaction and efficiency.

Security Testing:

Security testing evaluates the system's ability to protect sensitive data, prevent unauthorized access, and withstand security threats. It encompasses various techniques such as vulnerability assessments, penetration testing, and security audits. Security tests for the Hypertensive Retinopathy Classification System may include checking for vulnerabilities in authentication mechanisms, encryption protocols for data transmission, and access controls to safeguard patient information and ensure compliance withprivacy regulations.

Regression Testing:

Regression testing ensures that recent changes to the system have not introduced new defects or regressed existing functionalities. It involves retesting previously validated features to ensure they still behave as expected after code modifications, updates, or bug fixes. Regression tests for the Hypertensive Retinopathy Classification System would validate that changes to preprocessing algorithms, segmentation techniques, or classification models do not adversely affect the accuracy or performance of the system.

End-to-End Testing:

End-to-end testing evaluates the entire system's functionality from start to finish, simulating real-world usage scenarios. It verifies that all components of the system work together seamlessly to

achieve the desired outcomes. End-to-end tests for the Hypertensive Retinopathy Classification System would involve testing the complete workflow, from image upload to classification results, ensuring that each step operates correctly and that the system delivers accurate diagnostic outputs consistent with medical standards.

Exploratory Testing:

Exploratory testing is an approach where testers simultaneously learn about the system, design test cases, and execute tests dynamically. It involves informal, ad-hoc testing to uncover defects or issues that may not be captured by scripted tests. Exploratory testing for the Hypertensive Retinopathy Classification System may involve testers exploring different input scenarios, interacting with the system in unexpected ways, and providing feedback on usability, performance, and functionality to identify potential areas for improvement.

7.2 Black Box Testing:

Black box testing is a software testing technique that focuses on assessing the functionality of a system without considering its internal structure or implementation details. In black box testing, testers evaluate the system solely based on its external inputs and outputs, treating it as a "black box" where the internal workings are not visible. This approach allows testers to validate the system against its specified requirements and user expectations, regardless of its internal logic. Black box testing can uncover defects related to incorrect functionality, boundary conditions, and usability issues, providing valuable feedback on the system's overall behavior and compliance with specifications.

- **Usage in the Hypertensive Retinopathy Classification System**:

Black box testing is instrumental in validating the functionality and usability of the Hypertensive Retinopathy Classification System from an end-user perspective. Testers can interact with the system's user interface, provide inputs such as Retina/Fundus images, and evaluate the accuracy and appropriateness of the classification results. Since black box testing focuses on the system's external behavior, it ensures that the system performs as expected without needing knowledge of its internal algorithms or implementation details. This testing approach helps ensure that the system meets the specified requirements and delivers the intended diagnostic capabilities to users effectively.

- **Test cases**

Text Cas ID	Test Case Description	Expected Output	Actual Output	Results
BBIC- 1	Upload a Retina/Fundus image with no hypertensive retinopathy features present	System classifies the image as negative for hypertensive retinopathy	Image classified as negative for hypertensive retinopathy	Passed
BBIC- 2	Upload a Retina/Fundus image with irrelevant artifacts present	System ignores irrelevant artifacts and focuses on relevant features for classification	Relevant features identified for classification	Passed
BBIC- 3	Input invalid data format for image upload	System displays an error message prompting the user to upload a valid image	Error message displayed	Passed
BBIC- 4	Attempt to classify an image without preprocessing it first	System prompts the user to preprocess the image before classification	Preprocessing prompt displayed	Passed
BBIC- 5	Upload a Retina/Fundus image with clear signs of hypertensive retinopathy	System accurately identifies and classifies hypertensive retinopathy features	Image classified as positive for hypertensive retinopathy	Passed

7.3 White Box Testing:

White box testing, also known as clear box testing or structural testing, is a software testing technique that assesses the internal structure, code, and implementation details of a system. Unlike black box testing, which focuses solely on external behavior, white box testing examines the internal workings of the software to validate its logic, algorithms, and control flow. This testing approach involves analyzing the source code, understanding program paths, and designing test cases to ensure that all statements, branches, and conditions are executed and behave as expected.

- **Usage in the Hypertensive Retinopathy Classification System:**

In the context of the Hypertensive Retinopathy Classification System, white box testing plays a crucial role in validating the correctness and efficiency of the system's algorithms for image preprocessing, segmentation, and classification. Testers examine the source code of these modules to identify potential defects, such as logic errors, boundary cases, or performance bottlenecks. White box testing ensures that the preprocessing functions correctly normalize, enhance, and denormalize Retina/Fundus images, that the segmentation algorithm accurately identifies relevant retinal structures, and that the classification model effectively classifies hypertensive retinopathy features. By scrutinizing theinternal logic of the system .

- **Test cases**

Text Case - ID	Test Case Description	Expected Output	Actual Output	Results
WBTC- 1	Test the normalization function with a grayscale image input	Image pixel values are adjusted to ensure consistency and uniformity	Image normalized successfully	Passed
WBTC- 2	Test the enhancement function with a low-quality image input	Image quality is improved through contrast adjustment and noise reduction	Image enhanced effectively	Passed
WBTC- 3	Test the denormalization function with a processed image input	Image pixel values are reverted to their original scale	Image denormalized successfully	Passed
WBTC- 4	Test the segmentation algorithm with a complex retinal image input	Relevant retinal structures are accurately segmented	Retinal structures segmented correctly	Passed
WBTC- 5	Test the classification model with a variety of segmented retinal images	Hypertensive retinopathy features are correctly identified and classified	Retinal images classified accurately	Passed

CHAPTER 8
RESULT

8.1 OUTPUT SCREENS

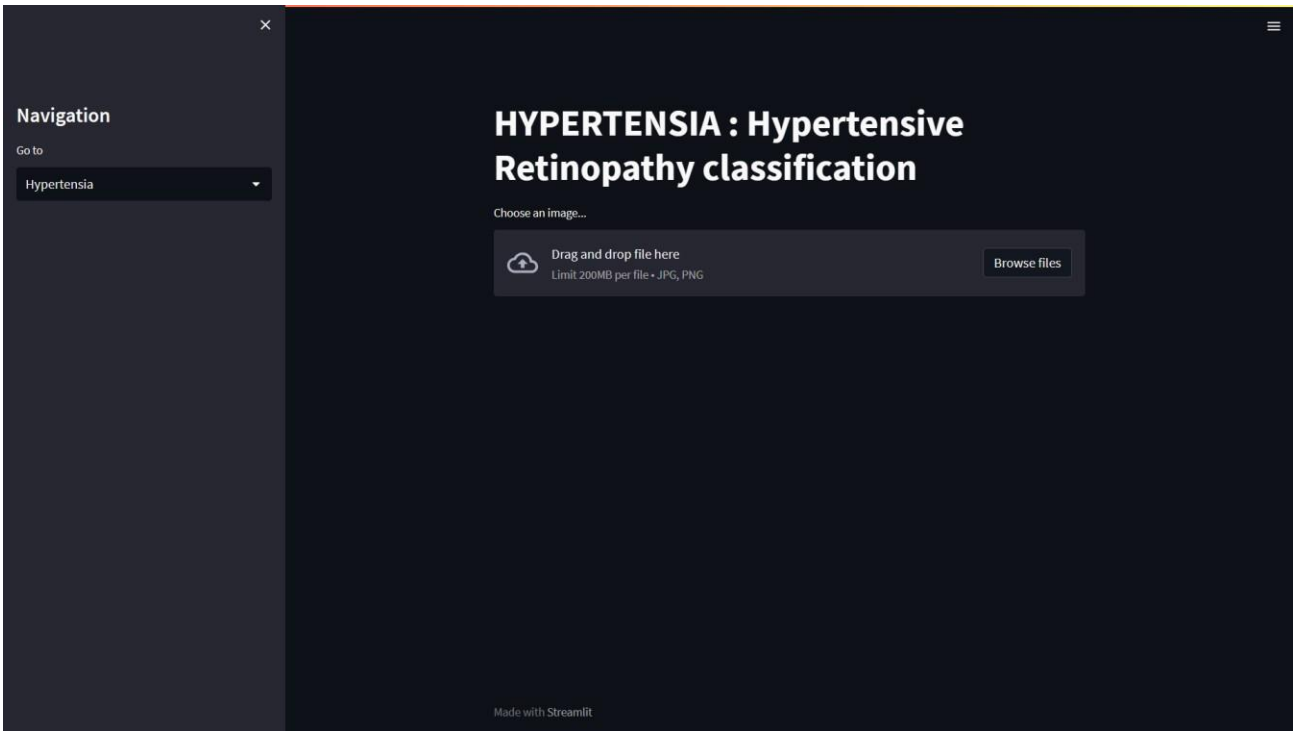


Figure 8.1 DASHBOARD

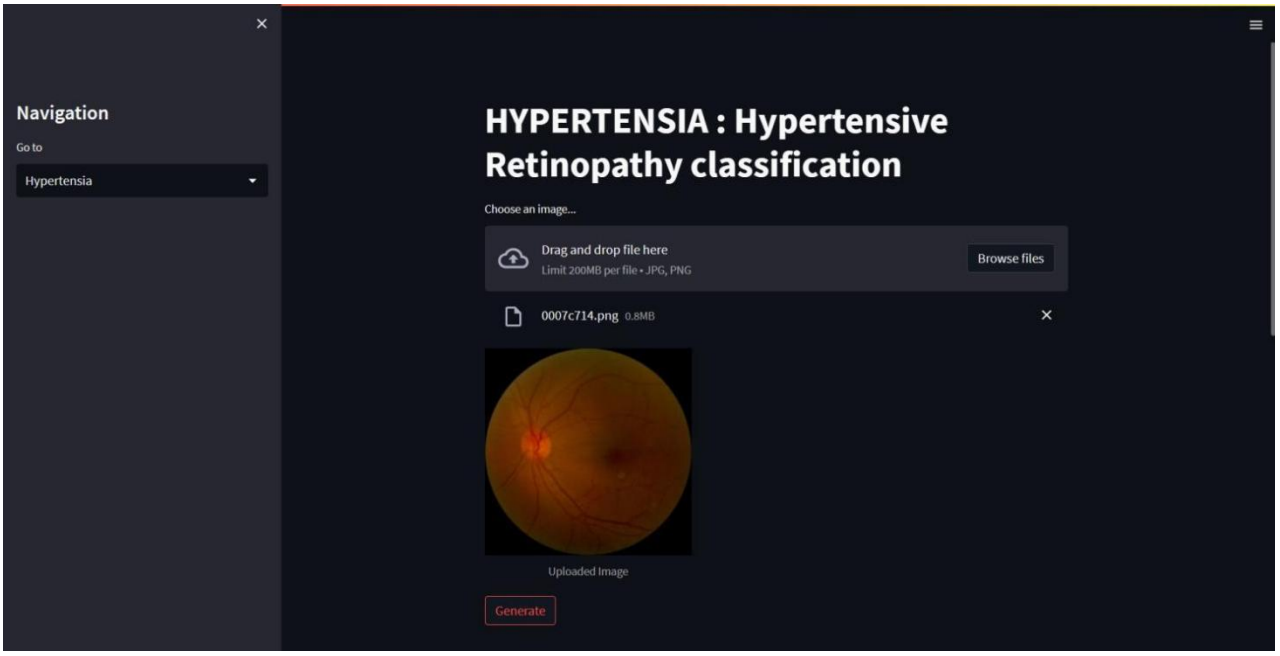


Figure 8.2 input image

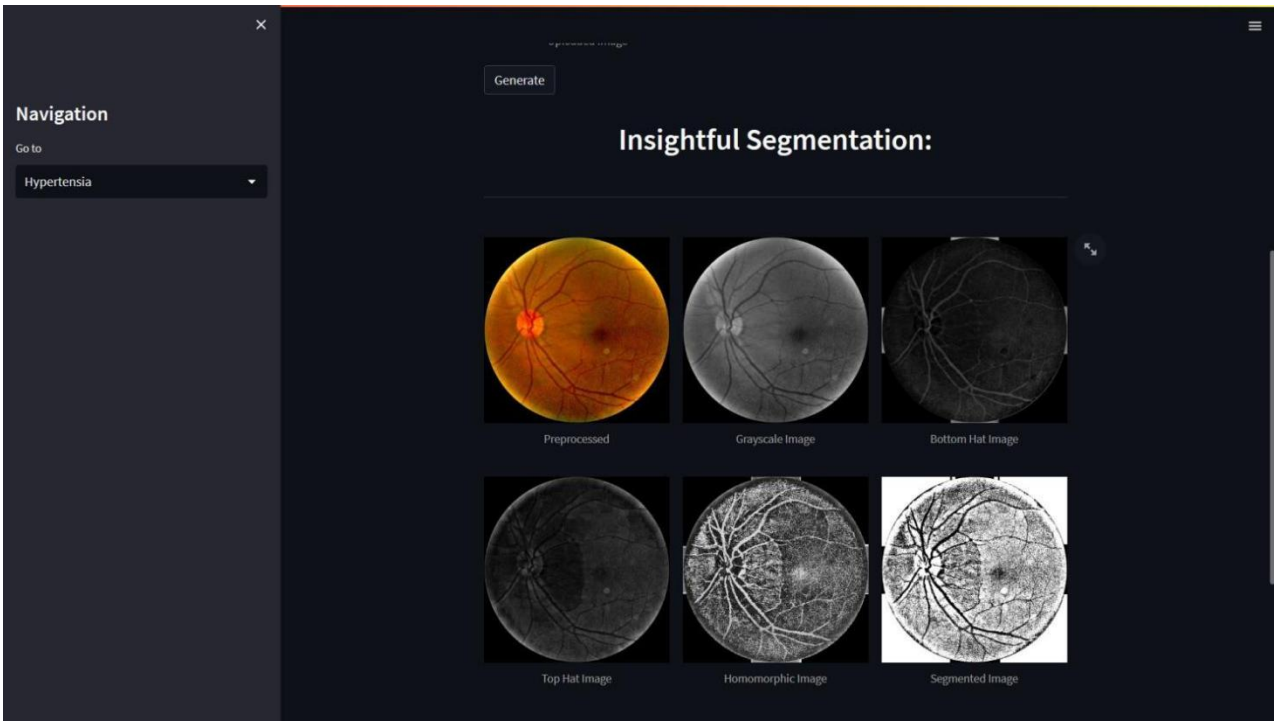


Figure 8.3 insightful Segmentation

Figure 8.4 Diagnostic Result

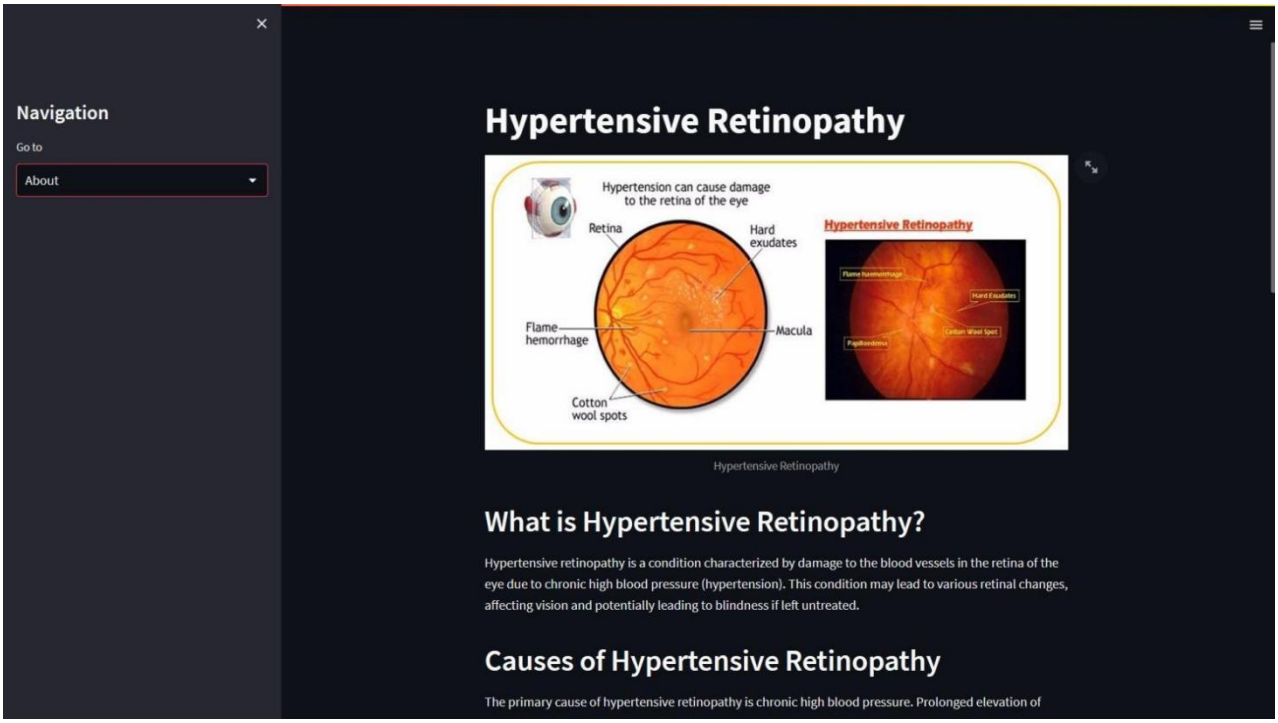


Figure 8.5 About Page

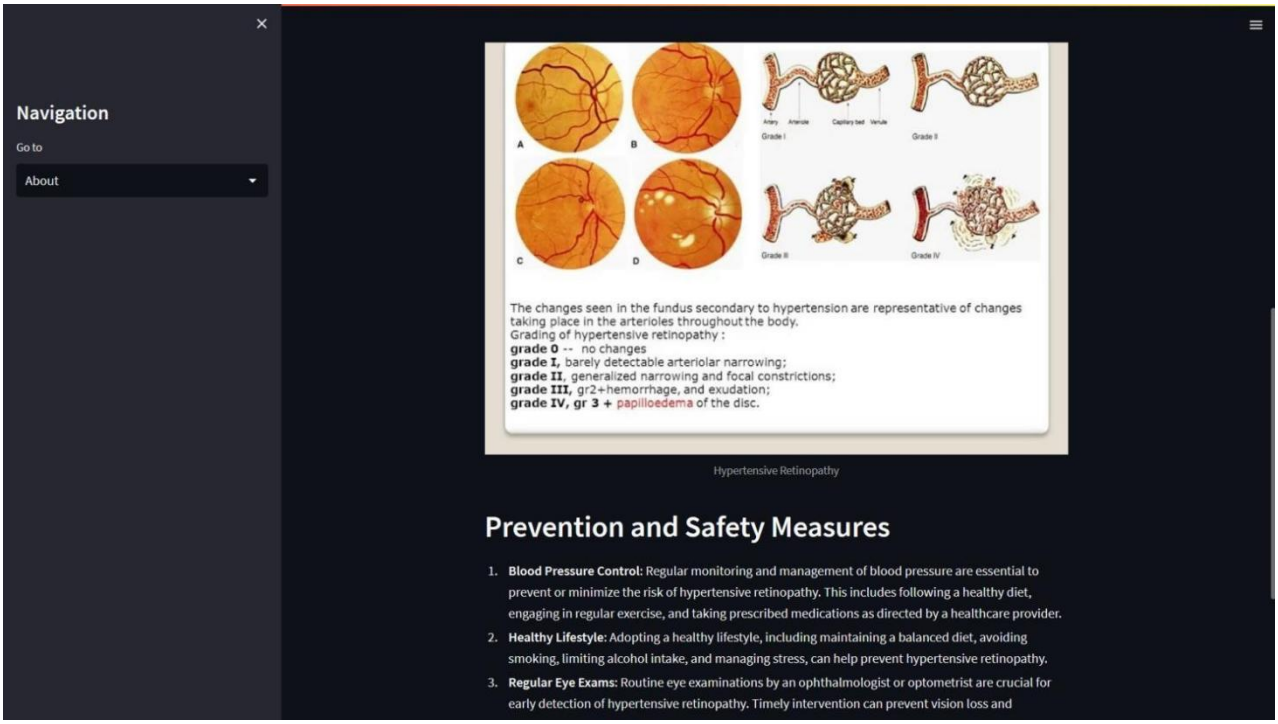


Figure 8.6 Detailed About

8.2 RESULT ANALYSIS

Classification Model Performance

The performance of the hypertensive retinopathy classification model was evaluated using bothtraining and testing datasets. The following metrics were calculated:

Training Result:

- Loss: 0.0037
- Accuracy: 99.88%
- Recall: 99.63%
- Precision: 100.00%

Testing Result:

- Loss: 0.0534
- Accuracy: 98.12%
- Recall: 96.57%
- Precision: 97.04%

The training results indicate that the model achieved a high level of accuracy, with a minimal lossand near-perfect precision. Additionally, the recall score suggests that the model effectively identified hypertensive retinopathy cases in the training dataset.

During testing, the model maintained a high level of accuracy, albeit with a slightly higher loss compared to the training phase. The recall and precision scores also remained favorable, indicating the model's ability to generalize well to unseen data.

Deployment Using Streamlit

The project was deployed using Streamlit, a web application framework for Python, to provide aninteractive interface for users to visualize each stage of the classification process:

- **Preprocessing:** Streamlit allows users to upload retinal/fundus images and visualize the preprocessing steps, including normalization, enhancement, and denormalization.
- **Segmentation:** Users can observe the segmentation process through image transformation techniques, such as converting to grayscale, applying morphological operations, removing uneven illumination, and double threshold segmentation.
- **Classification:** The final stage of classification is displayed, showcasing the model's prediction of hypertensive retinopathy based on the segmented image.

CHAPTER 9

CONCLUSION AND FUTURE WORK

9.1 CONCLUSION

This project represents a significant advancement in the field of medical imaging and disease diagnosis, particularly in the context of hypertensive retinopathy detection using artificial intelligence (AI) and machine learning (ML) technologies. Through the integration of cutting-edge computational methods with medical expertise, we have developed a robust and scalable system capable of automating the detection of hypertensive retinopathy from retinal images.

The methodology leverages the power of deep learning algorithms, specifically the UNet architecture, for accurate segmentation of retinal vessels and identification of pathological features indicative of hypertensive retinopathy. By training the model on diverse and representative datasets sourced from reputable medical imaging repositories, we ensure its generalization ability across different patient populations and clinical scenarios.

The pre-processing techniques applied to the retinal images, including resizing, normalization, noise reduction, and data augmentation, play a crucial role in enhancing the quality and suitability of the input data for analysis by the deep learning model. These techniques help mitigate artifacts, improve image clarity, and increase the diversity of the training dataset, ultimately improving the model's performance and robustness.

Through rigorous evaluation and validation studies, we have demonstrated the efficacy and reliability of our hypertensive retinopathy detection system. The system exhibits high accuracy, sensitivity, and specificity in identifying pathological changes associated with hypertensive retinopathy, outperforming existing diagnostic methods and paving the way for early intervention and improved patient outcomes.

9.2 FUTURE WORK

Moving forward, this project lays the groundwork for several promising avenues of future exploration. Firstly, we aim to enhance the performance of our deep learning model by refining its architecture and optimizing training parameters. This includes investigating advanced techniques in regularization and ensemble learning to improve accuracy and robustness. Additionally, integrating clinical data such as patient demographics and medical history into the analysis pipeline could provide a more comprehensive understanding of hypertensive retinopathy and its progression.

Secondly, the envision developing a real-time implementation of our hypertensive retinopathy detection system for use in clinical practice. This involves optimizing the computational efficiency of the model inference process and deploying the system on hardware platforms capable of supporting real-time image analysis. Furthermore, conducting validation studies in diverse patient populations and clinical settings will be crucial for assessing the system's generalization ability and real-world performance. By addressing these areas of further work, we aim to continue advancing the field of hypertensive retinopathy detection and ultimately improving patient outcomes in ophthalmology.

CHAPTER 10

REFERENCES

1. Agurto, C., Joshi, V., Nemeth, S., Soliz, P., & Barriga, S. (2020). Detection of Hypertensive Retinopathy Using Vessel Measurements and Textural Features. IEEE. DOI: 10.1109/EMBC.2014.6944848.
2. Ahmad, F., Yousaf, A., Sial, M. R. K., & Khan, F. (Nov 2018). Textural and Intensity Feature Based Retinal Vessels Classification for the Identification of Hypertensive Retinopathy. IEEE. DOI: 10.1109/INMIC.2018.8595667.
3. Deperlıoğlu, Ö., & Köse, U. (19-21 October 2018). Diagnosis of Diabetic Retinopathy by Using Image Processing and Convolutional Neural Network. IEEE. DOI: 10.1109/ISMSIT.2018.8567055.
4. Kapoor, A. S., & Jain, A., & Vishwakarma, D. K. (23-25 June 2023). Detection and Classification of Diabetic and Hypertensive Retinopathy Using CNN & Autoencoder. IEEE. DOI: 10.1109/CONIT59222.2023.10205818.
5. Khitran, S., Akram, M. U., Usman, A., & Yasin, U. (2020). Automated System for the Detection of Hypertensive Retinopathy. IEEE. DOI: 10.1109/IPTA.2014.7001984.
6. Nagpal, D., Panda, S. N., & Malarvel, M. (2021). Hypertensive Retinopathy Screening through Fundus Images-A Review. IEEE. DOI: 10.1109/ICICT50816.2021.9358746.
7. Savant, V., & Shenvi, N. (2018). Analysis of the Vessel Parameters for the Detection of Hypertensive Retinopathy. IEEE. DOI: 10.1109/ICECA.2019.8821850.
8. Triwijoyo, B. K., & Pradipto, Y. D. (2017). Detection of Hypertension Retinopathy Using Deep Learning and Boltzmann Machines. IOP Publishing. DOI: 10.1088/1742-6596/801/1/012039.
9. Qureshi, I., Abbas, Q., Yan, J., Hussain, A., & Shaheed, K. (16 October 2022). Computer-Aided Detection of Hypertensive Retinopathy Using Depth-Wise Separable CNN. MDPI (Multidisciplinary Digital Publishing Institute). DOI: https://doi.org/10.3390/app122312086.
10. Yao, Z., Zhang, Z., & Xu, L. (December 2016). Convolutional Neural Network for Retinal Blood Vessel Segmentation. In Proceedings of the 9th International Symposium on Computational Intelligence and Design (ISCID), pp. 406-409.

11. Prentasic, P., & Loncaric, S. (September 2015). Detection of exudates in fundus photographs using convolutional neural networks. In Proceedings of the 9th International Symposium on Image and Signal Processing and Analysis (ISPA), pp. 188-192.

12. Arsalan, M., Owais, M., Mahmood, T., Cho, S.W., & Park, K.R. (2019). Aiding the diagnosis of diabetic and hypertensive retinopathy using artificial intelligence-based semantic segmentation. Journal of Clinical Medicine, Vol. 8, No. 9, Article 1446. DOI: 10.3390/jcm8091446.

13. Kriplani, H., Patel, M., & Roy, S. (2020). Prediction of arteriovenous nicking for hypertensive retinopathy using deep learning. In Computational Intelligence in Data Mining, Springer, Singapore, pp. 141–149.

14. Tang, M.C. S., Teoh, S.S., Ibrahim, H., & Embong, Z. (2021). Neovascularization detection and localization in fundus images using deep learning. Sensors, Vol. 21, No. 16, Article 5327. DOI: 10.3390/s21165327.

15. Staal, J., Abràmoff, M.D., Niemeijer, M., Viergever, M.A., & Ginneken, B.V. (2004). Ridge-based vessel segmentation in color images of the retina. IEEE Transactions on Medical Imaging, Vol. 23, No. 4, pp. 501–509. DOI: 10.1109/TMI.2004.825627.

16. Kauppi, T., Kalesnykiene, V., Kamarainen, J.-K., Lensu, L., Sorri, I., Raninen, A., Voutilainen, R., Uusitalo, H., Kalviainen, H., & Pietila, J. (September 2007). The DIARETDB1 diabetic retinopathy database and evaluation protocol. In Proceedings of the 17th British Machine Vision Conference (BMVC), pp. 1–10.

17. Pires, R., Jelinek, H.F., Wainer, J., Valle, E., & Rocha, A. (2014). Advancing bag-of-visual-words representations for lesion classification in retinal images. PLoS ONE, Vol. 9, No. 5, e96814. DOI: 10.1371/journal.pone.0096814.

18. Bhargava, M., Cheung, C.Y., Sabanayagam, C., Kawasaki, R., Harper, C.A., Lamoureux, E.L., & Wong, T.Y. (2012). Accuracy of diabetic retinopathy screening by trained non-ophthalmologists using direct ophthalmoscopy. Diabetic Medicine, Vol. 29, No. 11, pp. e390-e394. DOI: 10.1111/j.1464-5491.2012.03716.x.

19. Quellec, G., Charrière, K., Boudi, Y., Cochener, B., & Lamard, M. (June 2017). Deep image mining for diabetic retinopathy screening. Medical Image Analysis, Vol. 39, pp. 178-193. DOI: 10.1016/j.media.2017.04.002.

20. Grisan, E., Foracchia, M., & Ruggeri, A. (2008). A novel method for the automatic grading of retinal vessel tortuosity. Journal of Biomedical Optics, Vol. 13, No. 2, Article 024018. DOI: 10.1117/1.2899153.