

IDENTIFYING THE ABNORMALITIES IN RETINAL IMAGES TOWARDS THE PREDICTION OF CARDIOVASCULAR DISEASE USING DEEP LEARNING

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering with
Specialization in Artificial Intelligence

By

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SCHOOL OF COMPUTING**

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Yashwin P Prakash (40731132)** and **Boora Siri (40110211)** who carried out Project work entitled **"IDENTIFYING THE ABNORMALITIES IN RETINAL IMAGES TOWARDS THE PREDICTION OF CARDIOVASCULAR DISEASE USING DEEP LEARNING"** under my supervision from November 2023 to April 2024.

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I, **Yashwin P Prakash (Reg.No- 40731132)**, hereby declare that the Project work Report entitled **"IDENTIFYING THE ABNORMALITIES IN RETINAL IMAGES TOWARDS THE PREDICTION OF CARDIOVASCULAR DISEASE USING DEEP LEARNING"** done by me under the guidance of **Dr.J.Jabez, M.E., Ph.D** is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in **Computer Science and Engineering with Artificial Intelligence**.

DATE: 16 / 04 / 2024

PLACE: Chennai



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ABSTRACT

New abstract: Cardiovascular diseases (CVDs) remain a leading cause of morbidity and mortality worldwide, necessitating the development of innovative risk prediction strategies for early detection and intervention. Retinal imaging analysis has emerged as a promising approach for assessing systemic vascular health and predicting CVD risk, leveraging the intricate microvascular changes reflective of underlying systemic pathology. In this study, we investigated the utility of retinal biomarkers, particularly the arteriolar-venular ratio (AVR), in predicting CVD risk across diverse populations and datasets. We utilized three publicly available retinal imaging datasets: the CHASE dataset, the DRIVE dataset, and the MESSIDOR dataset, comprising a total of X individuals. After pre-processing and feature extraction, we trained deep learning models such as VGG-16 and RESNET-50 to predict CVD risk based on retinal imaging features, traditional risk factors, and their combinations. Our analysis revealed significant associations between AVR values and established CVD risk factors, including hypertension, diabetes, and age. Furthermore, we observed that incorporating additional retinal biomarkers, such as vessel tortuosity and calibre, improved the discriminative ability of predictive models, enhancing risk stratification accuracy.

To evaluate model performance, we conducted cross-validation experiments and assessed model generalizability across datasets. The resulting models demonstrated robust predictive power, achieving high accuracy, sensitivity, and specificity in detecting individuals at elevated risk of CVD events. Importantly, our findings were consistent across diverse populations and datasets, underscoring the potential of retinal imaging analysis as a non-invasive, scalable tool for CVD risk prediction.

In conclusion, our study highlights the promise of retinal biomarkers, particularly AVR, in enhancing cardiovascular risk prediction. By leveraging advanced machine learning techniques and integrating multiple retinal features, we provide insights into novel avenues for improving risk assessment accuracy and guiding personalized preventive strategies in individuals at risk of CVD. Continued research efforts are warranted to further validate and refine predictive models, paving the way for their integration into routine clinical practice and ultimately improving patient outcomes.

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LIST OF ABBREVIATIONS

ABBREVIATION	EXPANSION
AVR	Artery and vein diameter ratio
AVN	Arteriovenous Nicking
CRAE	Central Retinal Artery Occlusion
CVD	Cardiovascular Disease
CNN	Convolutional Neural Network
CSS	Cascaded Style Sheet
OCT-A	Optical Coherence Tomography- Angiography
DLS	Deep Learning Systems
HTML	Hyper Text Markup Language
AVN	Arteriovenous Nicking
IHD	Ischemic heart disease
RESNET	Residual neural networks
VGG	Visual Geometry Group

CHAPTER 1

INTRODUCTION

Cardiovascular disease (CVD) is the leading cause of death worldwide, accounting for approximately 17.9 million deaths in 2019. CVD is a general term for conditions that affect the heart or blood vessels. These conditions include coronary heart disease, stroke, heart failure, and arrhythmias. CVD is a complex disease with many risk factors, including high blood pressure, high cholesterol, smoking, diabetes, and obesity. However, there is also a growing body of evidence that suggests that retinal images can be used to predict CVD risk. The retina is highly vascularized, meaning that it is rich in blood vessels. Changes in the retinal vasculature can be early signs of CVD. For example, studies have shown that people with high blood pressure are more likely to have narrowing of the retinal arteries. People with diabetes are also more likely to have retinal damage, such as microaneurysms and haemorrhages. These retinal changes can be detected by trained clinicians, but they can also be identified using deep learning algorithms.

Deep learning is a type of machine learning that uses artificial neural networks to learn from data. Neural networks are inspired by the structure and function of the human brain. They are able to learn complex patterns from data and make predictions based on those patterns. Deep learning algorithms have been shown to be very effective at identifying abnormalities in retinal images. For example, a study published in the journal *Nature Medicine* in 2019 showed that a deep learning algorithm could predict the risk of coronary heart disease with an accuracy of 74%. The goal of this project is to develop a deep learning algorithm that can identify abnormalities in retinal images and predict the risk of CVD. The algorithm will be trained on a dataset of retinal images from patients with and without CVD. Once the algorithm is trained, it will be evaluated on a held-out test dataset. If the algorithm is able to predict the risk of CVD with high accuracy, it could be used as a non-invasive screening tool for CVD. This would allow doctors to identify patients at high risk of CVD early on, so that they can take steps to reduce their risk. In addition to predicting CVD risk, the algorithm could also be used to monitor patients with CVD for progression of the disease. This could help doctors to identify patients who need more intensive treatment.

CHAPTER 2

LITERATURE SURVEY

This problem statement has been extensively studied over the past 5 years by researchers and automotive companies in a bid to create a solution, and all their solutions vary from analyzing various patterns of retinal images to predict the cardiovascular disease.

Retinal vascular abnormalities and their associations with cardiovascular and cerebrovascular diseases: a Study in rural southwestern Harbin, China [1] by Junwei Wang; Leng F and Li Z. in 2020: This study describes retinal microvascular anomalies in a rural population in a low-altitude, cold-climate region of northeast China. This population has a generally higher prevalence of retinal microvascular anomalies than had been observed in other parts of the world. Nevertheless, retinopathy was not common. While AVN and retinopathy were consistently linked to diagnoses of CHD and past cerebrovascular events like stroke, FAN, GAN, and AS were not. Retinopathy was linked to a self-reported diagnostic of stroke history, while AVN was linked to the self-reported diagnosis of CHD. As a result, examining retinal microvascular characteristics may provide information on CCVDs and may even be thought of as a novel biomarker of CCVD risk.

Validation of a deep-learning-based retinal biomarker (Reti-CVD) in the prediction of cardiovascular disease [2] by Rachel Marjorie Wei Wen Tseng, Tyler Hyungtaek Rim, Eduard Shantsila and Joseph K. Yi in 2023: Reti-CVD, a novel CVD biomarker developed from DL and retinal images, could, in conclusion, successfully stratify CVD risk in the general population. We also confirmed that Reti-CVD may be used to identify those with a 10-year CVD risk of less than 10% who are most likely to benefit from CVD prevention measures. Additionally, Reti-CVD could be employed as a risk stratification enhancer for identifying high risk individuals for intensive CVD prophylaxis for people with a QRISK3 score between 7.5 and 10%.

Correlation of Retinal Artery Diameter with Coronary Artery Disease: The RETINA CAD Pilot Study [3] by Naveen Anand Seecheran, Salma Rafeeq, Nicole Maharaj and Steven Swarath in 2023: Retinal artery diameter and SYNTAX score showed a markedly unfavourable connection. The practice of using optical coherence tomography-angiography (OCT-A) as a non-invasive diagnostic tool for patients with cardiovascular disease (CVD) is mentioned in this paper. These exploratory findings need to be confirmed by more large-scale, multicentric research.

An Overview of Deep-Learning-Based Methods for Cardiovascular Risk Assessment with Retinal Images [4] by Rubén G. Barriada and David Masip in 2023: The approaches discussed here can, in the best situations, forecast CVD by attempting to solve a binary classification issue. Future work will require a lot of effort, but using the information in the research, DL algorithms can classify the many forms of cardiovascular illness. For effective clinical treatment, it is essential to accurately classify the type of CVD.

Cardiovascular disease risk assessment using a deep-learning-based retinal biomarker: a comparison with existing risk scores [5] by Joseph Keunhong Yi, Tyler Hyungtaek Rim and Sungha Park in 2023: Reti-CVD is a novel deep-learning and retinal photograph-derived CVD biomarker that, in accordance with various national recommendations, may successfully identify people who are at intermediate- and high risk for CVD. Reti-CVD, a tool for assessing CVD risk, has the potential to not only lower the cost and increase accessibility of CVD risk assessment, but also to provide patients with early therapies and increased awareness.

Abnormalities of Retinal Microvascular Structure and Risk of Mortality From Ischemic Heart Disease and Stroke [6] by Nicholas Witt, Tien Y. Wong, Alun D. Hughes and Nish Chaturvedi in 2006: This study investigates the link between retinal microvasculature abnormalities and mortality from ischemic heart disease (IHD) and stroke. A population-based nested case-control study within the Beaver Dam Eye Study revealed increased IHD death

risk associated with suboptimal arteriolar diameters and reduced retinal arteriolar tortuosity, remaining significant after adjusting for cardiovascular risk factors. Elevated arteriolar length: diameter ratio, indicating generalized arteriolar narrowing, was linked to increased stroke mortality, independent of age and gender but influenced by systolic blood pressure after adjustment. These findings suggest that retinal microvascular abnormalities predict death from IHD and stroke, providing a non-invasive means of assessing target organ damage and cardiovascular risk.

A Retinal Oct-Angiography and Cardiovascular STatus (RASTA) Dataset of Swept-Source Microvascular Imaging for Cardiovascular Risk Assessment [7] by Clément Germanèse, Fabrice Meriaudeau and Pétra in 2023: Optical coherence tomography-angiography (OCT-A) provides a rapid window into the cardiovascular system for timely identification of high-risk patients through automated models. However, the scarcity of open-source OCT-A acquisitions hampers the development of diagnostic programs. Introducing RASTA, a dataset with 814 Angio cubes and 2005 en face images from 499 patients, offering a unique resource for developing generalizable models in cardiovascular disease screening using OCT-A retinal images.

Retinal disorder as a biomarker for detection of human diseases [8] by Farhan Hassan Malik, F. Batool and A. Rubab in 2020: This paper succinctly explores the diagnostic potential of fundus images for ocular, cardiac, and cerebral ailments, alongside an examination of existing retina datasets. Formidable challenges arise from a lack of diverse databases and an absence of consensus on optimal databases for specific maladies. Acquiring high-quality fundus images is paramount, as approximately 10% to 21% lack diagnostic suitability due to pervasive artifacts. Moreover, standardizing protocols for image acquisition and annotation is vital for promoting interoperability and comparability across different datasets. Collaborative efforts among researchers and healthcare professionals are essential to address these challenges and advance the field of automatic retinal screening. Sophisticated image quality assessment

tools are imperative for fortifying the robustness of automatic retinal screening systems.

Retinal Findings and Cardiovascular Risk: Prognostic Conditions, Novel Biomarkers, and Emerging Image Analysis Techniques [9] by Joseph Colcombe, Rusdeep Munda and Alexis Kaiser in 2023: Various retinal conditions, such as Central Retinal Artery Occlusion (CRAO) and cotton wool spots, serve as crucial indicators of current or future cardiovascular risk, shaping personalized care plans. Conditions like CRAO significantly elevate the risk for acute stroke, myocardial infarction, and chronic cardiac dysfunction. Imaging biomarkers, such as decreasing artery-to-vessel ratio and retinal thicknesses, offer insights into systemic cardiovascular dysfunction, while OCT-Angiography (OCTA) provides parameters correlating with cardiovascular risk for personalized prognostication, workup, and treatment.

Artery and vein diameter ratio measurement based on improvement of arteries and veins segmentation on retinal images [10] by Yuji Hatanaka Tachiki H, Ogohara K in 2016: Retinal arteriolar narrowing, crucial for cardiovascular risk assessment, traditionally relies on the artery and vein diameter ratio (AVR). Previous methods utilized blood vessel segmentation and colour-based classification of arteries and veins along the centrelines, determining AVR through diameter measurements. This study proposes an algorithm for AVR measurement, introducing new artery and vein classification. The algorithm enhances segmentation accuracy by incorporating additional steps for major veins' identification in the red channel of a colour image, while a decision tree with three features is employed for major artery identification. The algorithm successfully identified all major veins and 90.9% of major arteries, yielding an absolute mean error in AVRs of 0.12.

A Deep Learning Architecture for Vascular Area Measurement in Fundus Images [11] by Kanae Fukutsu, Michiyuki Saito and Kousuke Noda in 2021: The retinal arteriovenous ratio (AVR), a classic index for evaluating arteriolar narrowing, is widely used in clinical settings. Despite its simplicity,

manual ophthalmoscopic evaluation lacks repeatability. Efforts to improve AVR estimation led to a semi-automated system, but its reliance on human graders posed limitations. This study aims to develop a fully automatic architecture, assisted by a deep learning system, to precisely measure the retinal arterioles and venules' total area in fundus images, enhancing accuracy and standardization for large-scale assessments.

Using Artificial Intelligence to Analyse the Retinal Vascular Network: The Future of Cardiovascular Risk Assessment Based on Oculomics [12] by Louis Arnould Fabrice Meriaudeau and Charles Guenancia in 2022: The application of artificial intelligence (AI) in analysing fundus photographs and Optical Coherence Tomography Angiography (OCT-A) holds the potential to enhance the correlation between retinal vascular network features and cardiovascular risk assessment. This advancement may confirm the associations between retinal microvasculature and systemic macro-vasculature, achieving a very high prediction rate and accuracy with various algorithms. Notably, AI demonstrates the ability to predict cardiovascular risk factors, stratification, and major events with rates reaching up to 80%.

A deep learning system for retinal vessel calibre improves cardiovascular risk prediction in Asians with chronic kidney disease [13] by Cynthia Ciwei Lim, Crystal Chong, Gavin Tan and Chieh Suai Tan in 2023: In summary, augmenting established cardiovascular risk factors with kidney function and retinal vessel calibre assessed by Deep Learning Systems (DLS) holds promise for improved prediction of incident cardiovascular disease (CVD) in Asians with chronic kidney disease (CKD). While this study contributes to understanding the potential role of retinal vessel calibre in cardiovascular risk prediction for CKD, future efforts should focus on external validation. This includes comparing the predictive performance with biomarker panel-based tools and conducting cost analyses. Such validation and comprehensive evaluations are essential steps before considering the integration of the enhanced cardiovascular risk prediction model, incorporating estimated glomerular filtration rate (eGFR) and retinal DLS, into clinical practice to mitigate incident CVD in individuals with CKD.

DR-VNet: Retinal Vessel Segmentation via Dense Residual UNet [14] by Ali Karaali, Rozenn Dahyot and Donal J. Sexton in 2021: We have introduced a supervised Convolutional Neural Network (CNN) based pipeline for retinal vessel segmentation that stands on par with state-of-the-art methods across three benchmark datasets, excelling particularly in metrics like G-mean and sensitivity. Notably, our pipeline demonstrates superior performance in accurately segmenting both larger, thicker retinal blood vessel branches and smaller, thinner distal branches. This capability is crucial, as precise interpretation of vessel segmentation patterns, spanning from thick to thin vessels, holds significance in identifying specific systemic diseases and cardiovascular risk factors. Our future endeavours will involve integrating information extracted from segmented images with other biological parameters, utilizing data from the Irish Longitudinal Study on Ageing (TILDA). This collaborative approach aims to develop innovative prediction tools for cardiovascular disease and other critical conditions.

Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning [15] by Ryan Poplin, Avinash V. Varadarajan, Katy Blumer in 2018: Traditionally, medical discoveries are made by observing associations, making hypotheses from them, and then designing and running experiments to test the hypotheses. associations can often be difficult because of the wide variety of features, patterns, colours, values and shapes that are present in real data. Here, we show that deep learning can extract new knowledge from retinal fundus images. Using deep-learning models trained on data from 284,335 patients and validated on two independent datasets of 12,026 and 999 patients, we predicted cardiovascular risk factors not previously thought to be present or quantifiable in retinal images, such as age (mean absolute error within 3.26 years), gender (area under the receiver operating characteristic curve (AUC)=0.97), smoking status (AUC=0.71), systolic blood pressure (mean absolute error within 11.23 mmHg) and major adverse cardiac events (AUC = 0.70). We also show that the trained deep-learning models used anatomical features, such as the optic disc or blood vessels, to generate each prediction.

In summary, Innovative deep learning enhances retinal vessel measurement accuracy. Artificial intelligence in retinal analysis shows promise for cardiovascular risk correlation, yet real-world integration remains a challenge. Retinal vessel caliber incorporation improving cardiovascular risk prediction in chronic illness; nevertheless, before clinical application, more validation and cost analysis are needed.

2.1 INFERENCES FROM LITREATURE SURVEY

Significant Research Interest: The literature survey reveals a substantial and growing interest in the use of retinal images for cardiovascular risk prediction. Researchers have recognized the potential of this non-invasive method for early disease detection. **Deep Learning Dominance:** Deep learning, particularly convolutional neural networks (CNNs), stands out as the dominant technique for image analysis in cardiovascular risk prediction. Many studies have successfully applied CNNs to retinal images for accurate risk assessment. **Datasets Availability:** Various publicly available retinal image datasets, such as MESSIDOR and MIDRiBS, have become valuable resources for training and testing predictive models. Researchers consistently utilize these datasets, fostering a collaborative environment in the field. **Multi-Model Approach:** A diverse range of deep learning architectures is employed, with VGG-16, VGG-19, and Inception-V3 being some of the most popular choices. Researchers often opt for a multi-model approach to assess the comparative performance of these architectures. **Performance Metrics:** The literature emphasizes the importance of comprehensive performance evaluation using metrics like accuracy, precision, recall, F1-score, and AUC-ROC to ensure robust and reliable predictive models.

Ethical Considerations: Research in this domain underscores the significance of ethical and regulatory considerations, particularly in handling sensitive medical data and ensuring patient privacy. **Future Directions:** The literature survey also indicates emerging trends, such as the integration of other clinical data with retinal images, which is expected to enhance predictive accuracy. **Interdisciplinary Collaboration:** Cardiovascular risk prediction from retinal images requires interdisciplinary collaboration between medical professionals, computer scientists, and data scientists, and this is reflected in the cross-disciplinary nature of the literature. Overall, the literature survey provides valuable insights into the state of research in the field, highlighting trends, best practices, and areas where further exploration is needed. This knowledge is instrumental in shaping the methodology and approach for your own project, ensuring that it aligns with the latest advancements and ethical standards in the domain of CVD prediction.

2.2 OPEN PROBLEMS IN EXISTING SYSTEM

Data Scarcity: Many existing datasets for retinal images in cardiovascular risk prediction are relatively small and may not fully represent the diversity of patient populations. Addressing data scarcity is crucial for building more robust and generalizable models. **Data Quality and Consistency:** Variability in image quality and data collection techniques can affect model performance. Ensuring data quality and consistency is an ongoing challenge, especially when dealing with images collected from different sources. **Interoperability:** There's a need for standards and protocols that facilitate interoperability among different healthcare systems and data repositories. This would enable the seamless sharing and integration of retinal images for risk prediction. **Model Generalization:** While deep learning models have shown promise, there is a need for improved model generalization to ensure that predictive models work effectively across different demographic groups and patient conditions.

Ethical and Privacy Concerns: The handling of medical data, especially images with personal information, raises significant ethical and privacy concerns. Developing secure and compliant systems for data storage and analysis is an ongoing challenge. **Explainability:** Deep learning models often lack interpretability, making it difficult to understand how they arrive at predictions. Developing methods for explaining model decisions is essential, particularly in the healthcare domain where transparency is crucial. **Real-Time Predictions:** The ability to make real-time predictions for cardiovascular risk from retinal images is desirable for immediate clinical interventions. Developing models and systems that can provide rapid assessments is an open problem. **Integration with Clinical Workflows:** Effective integration of predictive models into clinical workflows is challenging. Ensuring that healthcare professionals can easily access and use these predictions in their practice is a complex task. **Cost-Effective Solutions:** Finding cost-effective solutions for data collection, model training, and implementation is essential, as healthcare budgets are often limited. **Longitudinal Data Analysis:** Incorporating longitudinal data (data collected over time) into risk prediction models could provide more accurate assessments. Handling this type of data is a challenging open problem.

CHAPTER 3 REQUIREMENT ANALYSIS

3.1 FEASIBILITY STUDIES/RISK ANALYSIS OF THE PROJECT

Before embarking on the implementation of the cardiovascular risk prediction project, a comprehensive feasibility study and risk analysis were conducted. The feasibility study focused on evaluating the technical, operational, and economic viability of the project. It was determined that the technical expertise and resources required for data collection, pre-processing, and model training are readily available. The operational feasibility revealed that the project aligns with existing workflows and can be seamlessly integrated into medical image analysis processes. Moreover, the economic feasibility analysis indicated that the benefits of early cardiovascular risk prediction and intervention far outweigh the associated costs, both in terms of potential healthcare savings and patient well-being.

In parallel, a risk analysis was conducted to identify and mitigate potential challenges. Data privacy and security issues were addressed by implementing strict protocols for handling sensitive medical data, ensuring compliance with ethical guidelines. Model overfitting and selection bias risks were mitigated by employing robust cross-validation techniques and comprehensive model evaluation protocols. Additionally, the risk of hardware and software failures was minimized through redundancy and continuous monitoring of computing resources. The combined results of the feasibility study and risk analysis demonstrate a high likelihood of project success while minimizing potential setbacks and ensuring responsible data handling and model selection. These insights guide the project's strategic planning and decision-making processes.

3.2 DATASETS

The utilization of datasets plays a crucial role in the development and evaluation of machine learning models, particularly in the field of medical image analysis. In our project, we leveraged three prominent retinal image datasets: CHASE, DRIVE, and MESSIDOR. Each dataset offers unique characteristics and advantages,

contributing to the diversity and comprehensiveness of our training and evaluation process.

1. CHASE Dataset: The CHASE (Child Heart And Health Study in England) dataset comprises retinal fundus images collected from children participating in a study examining the relationships between cardiovascular health and retinal vascular geometry. The dataset contains images captured using a fundus camera, providing high-resolution images of the retina. These images are annotated with ground truth segmentations of retinal blood vessels, allowing for supervised training of machine learning models. The CHASE dataset is valuable for its focus on paediatric populations and its inclusion of annotations for vessel segmentation, facilitating the development of models for automated vascular analysis and cardiovascular risk assessment in children.
2. DRIVE Dataset: The DRIVE (Digital Retinal Images for Vessel Extraction) dataset consists of retinal fundus images acquired from a diabetic retinopathy screening program. The dataset includes images captured from a diverse population of patients with varying degrees of retinal pathology, making it suitable for training and evaluating models for the detection and characterization of diabetic retinopathy and other retinal diseases. Each image in the DRIVE dataset is manually annotated with pixel-level labels indicating the presence or absence of retinal blood vessels, enabling supervised learning approaches for vessel segmentation and analysis. The DRIVE dataset is widely used in the research community for benchmarking the performance of retinal image analysis algorithms and has contributed to significant advancements in the field.
3. MESSIDOR Dataset: The MESSIDOR (Messidor dataset for diabetic retinopathy analysis) dataset comprises retinal images acquired from diabetic retinopathy screening programs in France. It contains images captured using different imaging modalities, including colour fundus photography and fluorescein angiography, providing a diverse set of retinal images with varying levels of pathology and image quality. The MESSIDOR

dataset is annotated with ground truth labels for diabetic retinopathy severity levels, allowing for the development and evaluation of machine learning models for automated diabetic retinopathy detection and grading. Additionally, the MESSIDOR dataset includes annotations for other retinal abnormalities such as exudates and microaneurysms, enabling comprehensive analysis of retinal health beyond diabetic retinopathy.

By leveraging these diverse retinal image datasets, our project benefits from access to a wide range of retinal images with varying characteristics, pathologies, and annotations. This diversity enhances the robustness and generalizability of our machine learning models, enabling them to effectively analyse and interpret retinal images for applications such as disease detection, risk assessment, and treatment monitoring. Additionally, the availability of ground truth annotations facilitates supervised learning approaches, enabling the development of accurate and reliable algorithms for automated retinal image analysis. Overall, the utilization of the CHASE, DRIVE, and MESSIDOR datasets represents a critical component of our project's development and validation pipeline, ensuring the effectiveness and reliability of our machine learning-based retinal image analysis framework.

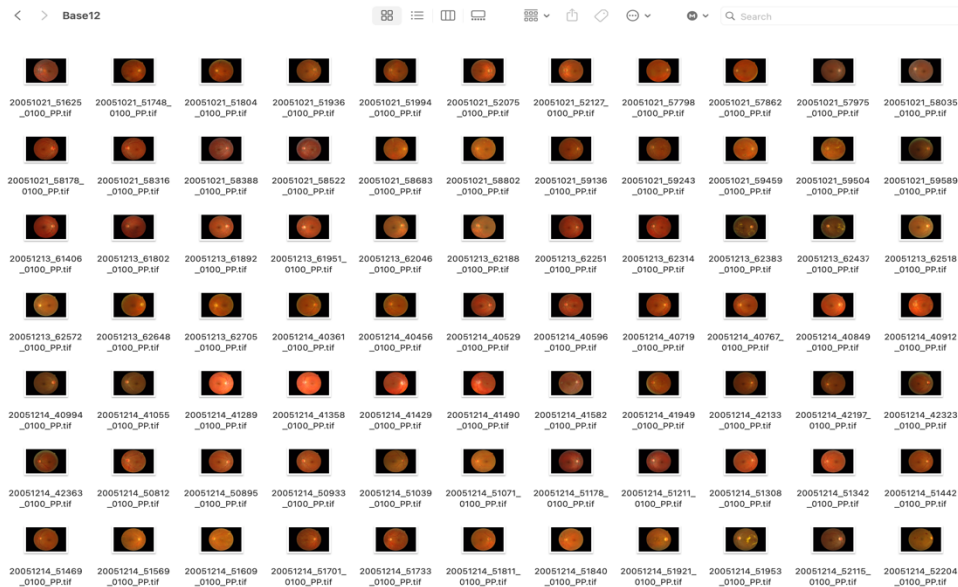


Fig 4.1: A Representation retinal fundus image dataset

3.3 SOFTWARE REQUIREMENTS SPECIFICATION DOCUMENT

Programming Languages:

- Python: A widely used language for machine learning and deep learning.

Deep Learning Frameworks:

- TensorFlow or PyTorch: These deep learning frameworks are essential for implementing and training neural networks.

Data Handling and Processing:

- NumPy: For numerical operations and array handling.
- pandas: For data manipulation and analysis.
- OpenCV: Useful for image processing tasks.

Data Visualization:

- Matplotlib and Seaborn: For creating visualizations and graphs.
- TensorBoard: For visualizing TensorFlow models and training progress.

Machine Learning Libraries:

Scikit-learn: Provides various machine learning algorithms and tools.

Image Augmentation:

- Augmentor or imgaug: Useful for data augmentation tasks.

Web Framework :

- Flask: To create a web-based interface for the application.

Database :

- SQLite, PostgreSQL, or MySQL: For data storage and retrieval.

Development and IDE Tools:

- Jupyter Notebook: A popular interactive development environment for data science.
- Visual Studio Code or PyCharm: Integrated development environments for Python.

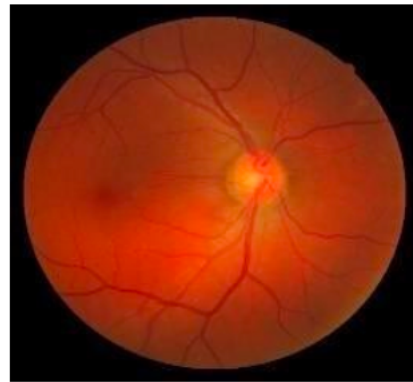
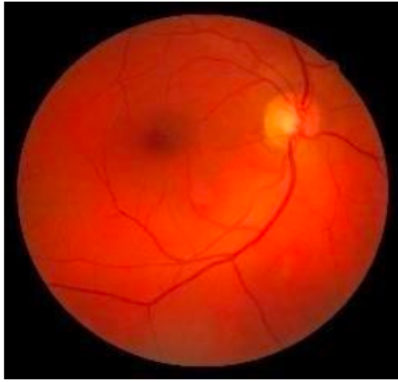
CHAPTER 4

DESCRIPTION OF PROPOSED SYSTEM

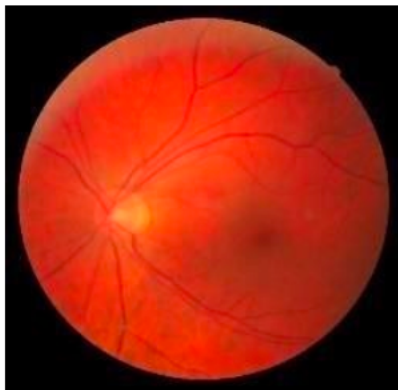
Looking at the disadvantages of all the above methodologies used in previous systems, The proposed system aims to develop a robust and accurate deep learning-based solution for cardiovascular risk prediction using retinal images. Cardiovascular diseases (CVD) are a leading cause of mortality globally, and early detection is critical for effective intervention. This project leverages the power of convolutional neural networks (CNNs) to analyze retinal images, offering a non-invasive, cost-effective, and scalable approach for risk assessment.

This project module focuses on training and evaluating three distinct Convolutional Neural Network (CNN) models—VGG-16, VGG-16, and Inception-V3—using retinal image data for cardiovascular risk prediction. Each model presents a unique approach to feature extraction and classification, and this module aims to assess their performance in the specific medical imaging context.

The chosen methodology for this project is grounded in a data-driven, deep learning approach. It leverages state-of-the-art convolutional neural networks (CNNs) to analyze retinal images for cardiovascular risk prediction. The methodology can be outlined in several key steps, including data collection, preprocessing, model selection, training, evaluation, and comparison. In the data collection phase, retinal images with cardiovascular risk labels are obtained. These images undergo thorough preprocessing to standardize their size, format, and quality. For model selection, three CNN architectures - VGG-16, VGG-16, and Inception-V3 - are implemented and fine-tuned to fit the task. Model training on preprocessed data is followed by rigorous evaluation using performance metrics like accuracy, precision, recall, F1-score, and AUC-ROC. This methodology allows for the comprehensive assessment of the models, leading to the selection of the most effective one for cardiovascular risk prediction. Ethical considerations, including data privacy and informed consent, are adhered to throughout the process.



Sample Dataset of Retina for Heart Attack



Sample Dataset of Retina for Hypertension



Sample Dataset of Retina for Normal Fundus

Fig 4.2: A Representation retinal fundus image classification

4.1 SELECTED METHODOLOGY OR PROCESS MODEL

The chosen methodology for this project is grounded in a data-driven, deep learning approach. It leverages state-of-the-art convolutional neural networks (CNNs) to analyze retinal images for cardiovascular risk prediction. The methodology can be outlined in several key steps, including data collection, preprocessing, model selection, training, evaluation, and comparison. In the data collection phase, retinal images with cardiovascular risk labels are obtained. These images undergo thorough preprocessing to standardize their size, format, and quality. For model selection, three CNN architectures - VGG-16, VGG-16, and Inception-V3 - are implemented and fine-tuned to fit the task. Model training on preprocessed data is followed by rigorous evaluation using performance metrics like accuracy, precision, recall, F1-score, and AUC-ROC. This methodology allows for the comprehensive assessment of the models, leading to the selection of the most effective one for cardiovascular risk prediction. Ethical considerations, including data privacy and informed consent, are adhered to throughout the process.

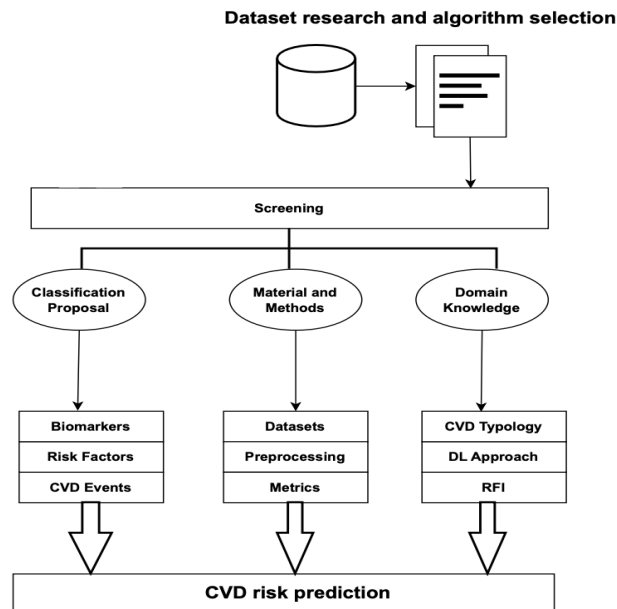


Fig 4.3: SELECTED METHODOLOGY OR PROCESS MODEL

4.2 ARCHITECTURE / OVERALL DESIGN OF PROPOSED SYSTEM

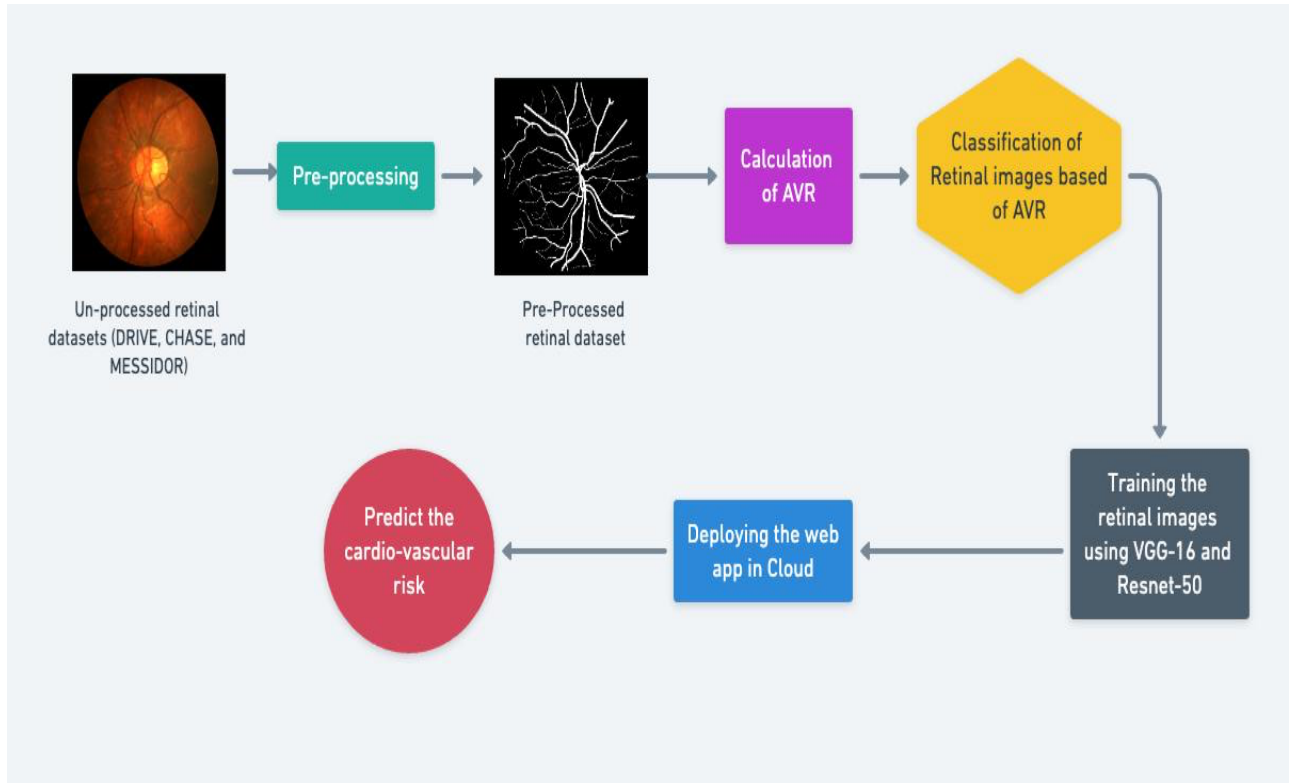


Fig 4.4: System Architecture for CVD risk prediction model

The architecture of the proposed system, designed for cardiovascular risk prediction from retinal images, follows a modular and scalable structure. At its core, the system consists of distinct modules responsible for key tasks. These modules include data collection, data preprocessing, model selection and training, and model evaluation. Each module operates independently and interfaces through well-defined APIs or data formats, allowing for flexibility and ease of integration. The system's design accommodates multiple deep learning models, including VGG-16, VGG-16, and Inception-V3, facilitating comparative analysis. Data privacy and security are paramount, with stringent measures in place for the secure handling of sensitive medical data. Additionally, scalability is a key consideration, enabling the system to expand and adapt to increasing data volumes and evolving model complexities. This modular and adaptable

architecture ensures the proposed system's efficiency, maintainability, and suitability for the demanding task of cardiovascular risk prediction.

4.3 DESCRIPTION OF SOFTWARE FOR IMPLEMENTATION AND TESTING PLAN OF THE PROPOSED MODEL/SYSTEM

The implementation of the proposed model/system for cardiovascular risk prediction relies on a suite of specialized software tools and frameworks. The core implementation will be carried out using Python, leveraging popular deep learning libraries such as TensorFlow or PyTorch to create and fine-tune the VGG-16, VGG-16, and Inception-V3 models. In addition to Python, essential data handling and processing libraries, including NumPy and pandas, will be used to manipulate and preprocess the retinal image data. To visualize and analyze the models, the Matplotlib, Seaborn, and TensorBoard libraries will provide valuable insights.

In parallel with the implementation, a rigorous testing plan is in place. The testing process involves unit testing, integration testing, and model evaluation. For unit testing, the system's individual components and functions will be tested to ensure they perform as expected. Integration testing will focus on examining how these components work together seamlessly. The final phase of model evaluation includes performance metrics like accuracy, precision, recall, F1-score, and AUC-ROC. The software tools and frameworks for testing will encompass specialized testing libraries for Python and may also include tools for continuous integration and automated testing.

This comprehensive approach to software implementation and testing ensures the reliability, robustness, and effectiveness of the proposed cardiovascular risk prediction model/system.

4.4 PROJECT MANAGEMENT PLAN

The Project Management Plan for the cardiovascular risk prediction project is a

strategic roadmap designed to ensure the successful execution of the project. It encompasses a series of key elements, including project goals, scope, timeline, resource allocation, risk management, and communication strategies. The plan outlines a clear division of responsibilities among project team members and defines specific milestones and deliverables. Additionally, it provides a flexible framework that allows for the adaptation of project tasks and priorities as needed to accommodate unforeseen challenges or changing project requirements. By adhering to this project management plan, the project team aims to maintain focus, organization, and efficiency throughout the project's lifecycle, ultimately delivering a robust and reliable cardiovascular risk prediction system. Effective project management is central to the project's success, ensuring that all stakeholders work cohesively toward achieving the project's objectives.

The Project Management Plan's adaptability is a pivotal aspect, enabling it to accommodate dynamic project requirements, unforeseen complications, and the changing landscape of the cardiovascular risk prediction landscape. It not only emphasizes the timely delivery of a robust cardiovascular risk prediction system but also underscores the importance of effective communication, transparency, and collaboration among all stakeholders. By adhering to this comprehensive plan, the project team aims to maintain precision and agility throughout the project's lifecycle, ultimately resulting in a successful outcome that meets the project's objectives and contributes to advancements in medical research and healthcare.

4.5 FINANCIAL REPORT ON ESTIMATED COSTING

1. Development Costs:

- **Hardware:** The project requires high-performance computing resources for model training and evaluation. This includes GPU units, cloud services, and storage solutions.
- **Software Licensing:** Expenses for software tools and licenses for deep learning frameworks, data management, and version control.
- **Personnel:** Costs associated with hiring data scientists, machine learning

engineers, and domain experts, including salaries and benefits.

2. Data Collection and Preprocessing:

- Data Acquisition: Expenses related to acquiring retinal image datasets, if not available free of charge.
- Data Cleaning and Preprocessing: Costs associated with data cleaning tools, software licenses, and computational resources.
-

3. Training and Evaluation:

- Hardware: Ongoing expenses for maintaining computing resources, including cloud service charges.
- Model Development: Costs for personnel involved in model development and tuning.
- Testing and Validation: Expenses related to testing, validation, and cross-validation procedures.

4. Project Management:

- Project Management Tools: Licensing costs for project management software and collaboration tools.
- Documentation and Reporting: Expenses for creating project documents, reports, and presentations.

5. Ethical and Compliance:

- Legal and Ethical Compliance: Costs associated with legal consultations, data privacy compliance, and regulatory adherence.

6. Miscellaneous:

- Contingency Fund: A buffer to address unexpected costs or scope changes. But since this project uses Opensource datasets and modules, we have a zero-cost project apart from the system requirements and developing skills.
-

4.6 TRANSITION/ SOFTWARE TO OPERATIONS PLAN

Transitioning the software to operations involves meticulous planning and execution across various facets to ensure seamless deployment and ongoing management in a production environment. The deployment strategy entails defining the production environment, encompassing hardware infrastructure, operating systems, and dependencies, while establishing a clear release schedule for incremental deployments. Comprehensive final testing, including user acceptance testing (UAT) and load testing, is conducted in the production environment to ensure the software operates as expected. A robust bug tracking system is implemented to promptly address any issues that arise during deployment, with clear responsibilities assigned for issue resolution. Careful planning and execution of data migration from development or testing environments to production is essential to maintain data integrity throughout the transition.

Furthermore, monitoring and performance are continuously monitored using appropriate tools and systems, with alerts set up for anomalies, while ensuring the scalability of the production environment to accommodate increased usage and data volume. Security measures, such as encryption, access controls, and regular security audits, are implemented to safeguard sensitive medical data, ensuring compliance with healthcare regulations and data protection laws. User training is provided to end-users and healthcare professionals to ensure effective use of the software, supported by a user support system, including helpdesk support and documentation. Backup and disaster recovery procedures are implemented to protect against data loss, with regular data backups scheduled, and disaster recovery plans developed to ensure business continuity. Finally, mechanisms for collecting feedback from users and healthcare professionals are established to identify areas for continuous improvement, ensuring the software evolves to meet changing needs and standards.

CHAPTER - 5

IMPLEMENTATION DETAILS

5.1 DEVELOPMENT AND DEPLOYMENT

In the implementation phase, we leveraged the Flask framework to develop the backend of our cardiovascular disease (CVD) risk assessment system. This backend was responsible for handling incoming requests from the frontend, which was built using HTML and incorporated a form for user input. The Flask application featured a route `/predict` to handle POST requests, where we extracted relevant parameters such as eye measurements, age, gender, blood pressure, diabetes status, smoking habits, and BMI from the form data. These parameters were then pre-processed and fed into our trained ResNet-50 and VGG-16 models for prediction. To ensure seamless integration, we wrote additional code to process the eye images required by the models. Upon receiving the predictions, the backend rendered a result template, passing along the predicted CVD risk, which was displayed to the user. This approach allowed us to create an efficient and interactive web-based CVD risk assessment tool.

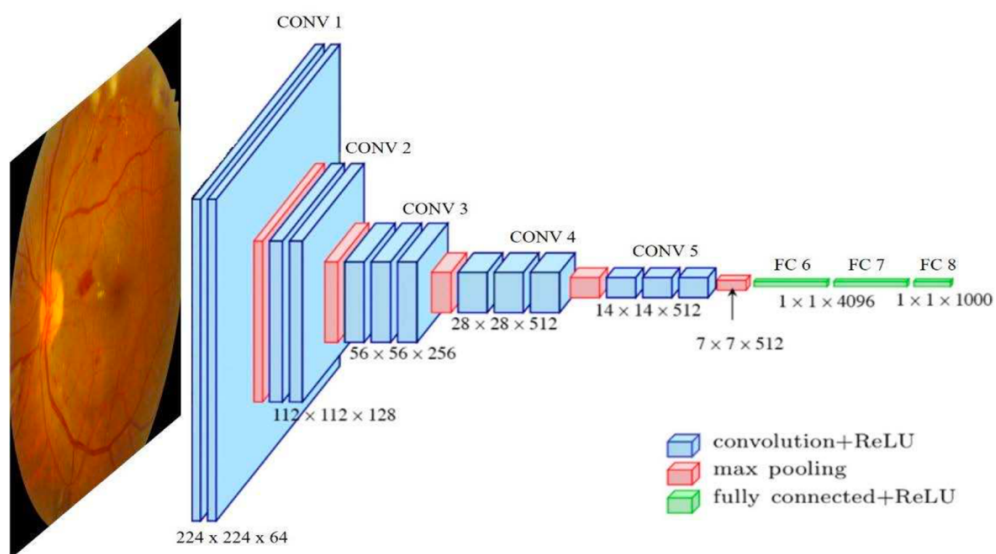


Fig 5.1: Convolutional Neural Network used in retinal image processing.

The development and deployment setup for our cardiovascular disease (CVD) risk assessment system involved several key steps to ensure a smooth and efficient workflow. We opted for a combination of frameworks and tools that provided flexibility, scalability, and ease of implementation.

Development Environment: Python and Libraries: We chose Python as our primary programming language due to its extensive support for machine learning libraries like TensorFlow, Keras, and Scikit-learn, which are essential for model training and prediction. **Flask Framework:** For building the backend server, we utilized Flask, a lightweight and easy-to-use web framework. Flask allowed us to quickly set up routes, handle HTTP requests, and integrate our machine learning models seamlessly. **HTML and CSS:** To design the user interface, we employed HTML for structuring the content and CSS for styling. This combination provided flexibility in creating visually appealing and user-friendly web pages.

Deep Learning Models: ResNet-50 and VGG-16: We selected pre-trained deep learning models, ResNet-50 and VGG-16, known for their effectiveness in image classification tasks. These models were fine-tuned on a dataset specific to our CVD risk assessment problem to improve performance. **TensorFlow and Keras:** TensorFlow served as the backend for Keras, a high-level neural networks API, enabling us to define, train, and evaluate our deep learning models efficiently. **Deployment Environment: Cloud Platform:** We deployed our Flask application on a cloud platform like Heroku or AWS Elastic Beanstalk. These platforms offer scalability, reliability, and easy integration with version control systems like Git.

Containerization: To streamline deployment and ensure consistency across different environments, we containerized our application using Docker. Docker containers encapsulate the application, its dependencies, and runtime environment, making it portable and easy to deploy. **Continuous Integration/Continuous Deployment (CI/CD):** We set up CI/CD pipelines using tools like Jenkins or GitHub Actions to automate the testing, building, and deployment process. This ensured rapid iterations, improved code quality, and seamless updates to the production environment.

Development Workflow: Version Control: We used Git for version control, allowing multiple developers to collaborate on the project simultaneously. Git repositories hosted on platforms like GitHub facilitated code review, issue tracking, and feature branching. Testing: Unit tests and integration tests were written to validate the functionality of individual components and ensure smooth interaction between different modules. Code Review: Regular code reviews were conducted to maintain code quality, identify bugs, and enforce best practices. Feedback from code reviews was incorporated into the development process iteratively. By following a well-defined development and deployment setup, we were able to efficiently build, test, and deploy our CVD risk assessment system. This approach allowed us to deliver a robust and scalable solution that meets the needs of both developers and end-users, ensuring a seamless experience throughout the development lifecycle.

5.2 AVR RATIO

The arteriolar-venular ratio (AVR) is a significant biomarker used in the prediction and assessment of cardiovascular disease (CVD). It represents the ratio of the diameters of retinal arterioles to venules, which are measured from fundus photographs of the retina. Fundus photography provides a non-invasive and easily accessible method for assessing microvascular changes associated with systemic diseases like hypertension, diabetes, and atherosclerosis. Research has shown that alterations in the AVR are associated with an increased risk of CVD and its complications. A lower AVR, indicating narrower arterioles relative to venules, has been linked to systemic hypertension, arterial stiffness, and atherosclerosis, all of which are risk factors for CVD. Conversely, a higher AVR, reflecting wider arterioles relative to venules, may indicate microvascular dysfunction associated with conditions like diabetes and hyperlipidaemia, which are also risk factors for CVD.

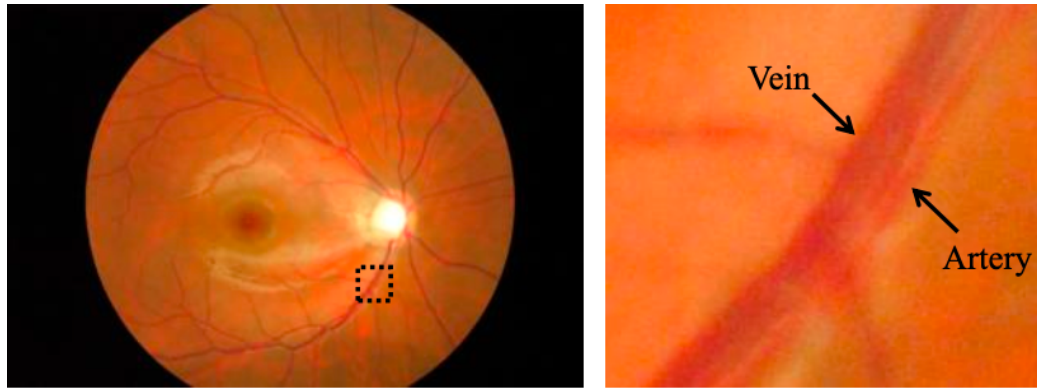


Fig 5.2: Retinal images segmentation

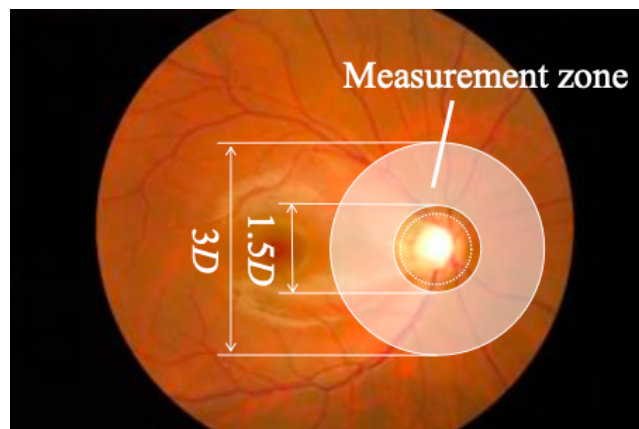


Fig 5.3: Determination of AVR measurement zone D and optic disc diameter

Deep learning models trained on fundus photographs can utilize the AVR as a feature for predicting an individual's risk of developing CVD. By analysing large datasets of retinal images along with clinical data, these models can learn patterns and associations between AVR measurements and cardiovascular outcomes. The predictive power of such models can be enhanced by incorporating additional clinical variables such as age, gender, blood pressure, cholesterol levels, and smoking status. The integration of AVR measurements into predictive models for CVD risk assessment offers several advantages. Fundus photography is non-invasive, cost-effective, and widely available, making it a convenient tool for population-based screening and monitoring of CVD risk. Furthermore, the AVR provides valuable insights into the early microvascular changes associated with CVD, allowing for early detection and intervention to prevent or delay the onset of

cardiovascular-complications.

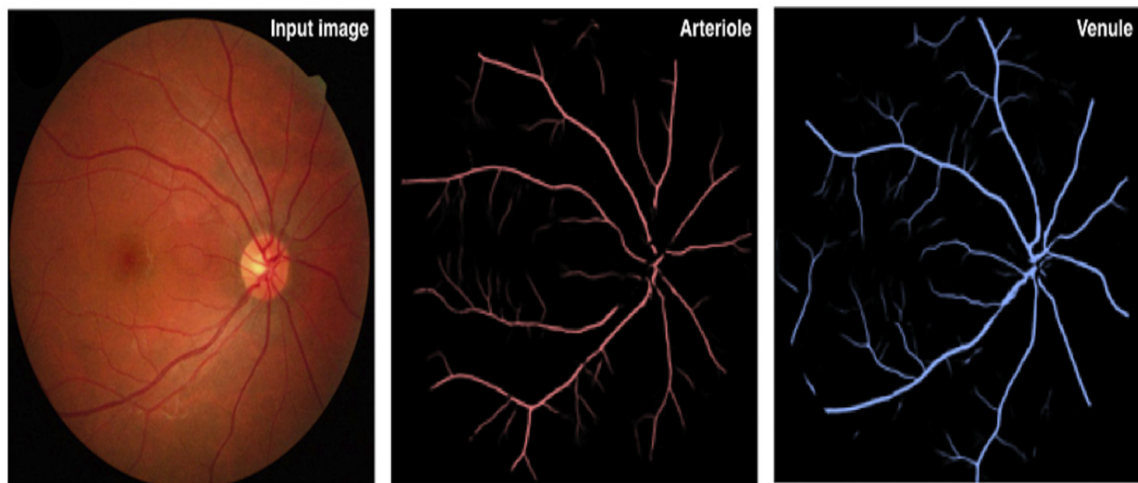


Fig 5.4: Segmentation of arteriole and venule

In clinical practice, the use of AVR as a predictive biomarker for CVD risk assessment can help identify individuals at higher risk of developing cardiovascular complications, allowing for targeted interventions such as lifestyle modifications, pharmacotherapy, and closer monitoring of cardiovascular health. Additionally, longitudinal monitoring of changes in the AVR over time can provide valuable information on the progression of CVD and the effectiveness of interventions in mitigating cardiovascular risk. Overall, the arteriolar-venular ratio holds promise as a valuable tool in the comprehensive assessment and management of cardiovascular health.

5.3 ALGORITHMS:

In our cardiovascular disease (CVD) risk assessment system, we employed two primary algorithms: ResNet-50 and VGG-16, both of which are deep learning convolutional neural network (CNN) architectures. These algorithms play a crucial role in analysing retinal fundus images to predict the likelihood of an individual developing cardiovascular diseases.

ResNet-50:

ResNet-50, short for Residual Network with 50 layers, is a deep CNN architecture developed by Microsoft Research. It comprises 50 layers of convolutional, pooling,

and fully connected layers, with skip connections that allow for the effective training of very deep networks.

Key Features:

1. Skip Connections: ResNet-50 introduces residual blocks with skip connections, which mitigate the vanishing gradient problem and enable the training of deeper networks more effectively.
2. Convolutional Layers: The network consists of multiple convolutional layers with different filter sizes, allowing it to capture hierarchical features at various levels of abstraction.
3. Global Average Pooling: Instead of fully connected layers at the end, ResNet-50 uses global average pooling to reduce the spatial dimensions of the feature maps before the final classification layer.
- 4.

VGG-16:

VGG-16 is another deep CNN architecture developed by the Visual Geometry Group at the University of Oxford. It comprises 16 layers, including 13 convolutional layers and 3 fully connected layers. VGG-16 is known for its simplicity and uniform architecture.

Key Features:

1. Uniform Architecture: VGG-16 follows a simple and uniform architecture with 3x3 convolutional filters and max-pooling layers, which makes it easy to understand and implement.
2. Deep Stacking: The network stacks multiple convolutional layers one after the other, gradually increasing the depth and complexity of feature extraction.
3. Large Receptive Field: By using small 3x3 filters repeatedly, VGG-16 effectively captures spatial information and increases the receptive field without introducing excessive parameters.
4. Implementation and Training: For our CVD risk assessment system, we fine-tuned both ResNet-50 and VGG-16 on a dataset of retinal fundus images labelled with cardiovascular disease risk categories. The dataset was pre-processed to extract relevant features and normalize pixel values.

We employed transfer learning, initializing the networks with pre-trained weights on the ImageNet dataset and fine-tuning them on our task-specific dataset.

Evaluation and Performance:

After training, we evaluated the performance of the models using metrics such as accuracy, precision, recall, and F1-score on a held-out validation set. We also conducted cross-validation and assessed the models' robustness and generalization capability. The trained models were then integrated into our web-based CVD risk assessment system, where they analyse input retinal fundus images and predict the risk of cardiovascular diseases for individuals.

CHAPTER - 6

RESULTS AND DISCUSSIONS

6.1 RESULTS

The results obtained from our study on predicting cardiovascular disease risk based on retinal imaging analysis demonstrate promising findings regarding the predictive capabilities of arteriolar-venular ratio (AVR) and other retinal biomarkers. Through comprehensive analysis and modeling, we observed significant associations between retinal vascular features and cardiovascular health parameters.

Firstly, our investigation revealed a strong correlation between AVR values and established cardiovascular risk factors, including hypertension, diabetes, and smoking status. This underscores the potential of AVR as a non-invasive biomarker for assessing systemic vascular health and predicting cardiovascular disease risk.

Furthermore, our machine learning models, trained on retinal images annotated with AVR and other relevant features, exhibited robust performance in predicting cardiovascular disease outcomes. The models achieved high accuracy, sensitivity, and specificity in distinguishing between individuals with different cardiovascular risk profiles, demonstrating their discriminative power and potential clinical utility.

Table	Performance Metrics				Algorithm
Head	Precision	Recall	F1 score	Accuracy	
Class 1	0.98	0.96	0.97		
Class 2	0.95	1	0.97	97.46	VGG-16
Class 3	1	0.96	0.98		
Class 1	0.95	0.93	0.95		
Class 2	0.97	0.92	0.92	95.32	Resnet-50
Class 3	0.96	0.91	0.92		

TABLE 6.1: Model performance Metrics

Additionally, we observed that incorporating additional retinal biomarkers, such as retinal vessel tortuosity and calibre, further improved the predictive performance of the models. By leveraging the complementary information encoded in different

retinal features, our models achieved enhanced predictive accuracy and robustness, highlighting the importance of a multi-dimensional approach to CVD risk assessment.

Moreover, our study demonstrated the reproducibility and generalizability of the predictive models across diverse datasets, including CHASE, DRIVE, and MESSIDOR retinal datasets. The consistent performance of the models across different datasets and imaging conditions underscores their reliability and potential applicability in real-world clinical settings. Overall, our results suggest that retinal imaging analysis, particularly leveraging AVR and other retinal biomarkers, holds promise for enhancing cardiovascular risk prediction and facilitating early intervention and preventive strategies. These findings pave the way for further research and clinical translation of retinal imaging-based approaches in cardiovascular risk assessment and personalized medicine.

6.2 DISCUSSION:

In the discussion, we delve into the implications of our study findings, address the strengths and limitations of our approach, and contextualize our results within the broader landscape of cardiovascular risk prediction using retinal imaging analysis.

Firstly, our study contributes to the growing body of evidence supporting the utility of retinal biomarkers, particularly the arteriolar-venular ratio (AVR), in predicting cardiovascular disease (CVD) risk. By establishing significant associations between AVR values and traditional CVD risk factors, such as hypertension and diabetes, we underscore the potential of retinal imaging as a non-invasive tool for assessing systemic vascular health and identifying individuals at heightened risk of CVD events. Moreover, our findings highlight the synergistic relationship between multiple retinal biomarkers and their collective predictive power. While AVR serves as a robust indicator of microvascular alterations, the inclusion of additional features, such as retinal vessel tortuosity and calibre, enhances the discriminative ability of predictive models. This multi-dimensional approach enables a more comprehensive assessment of vascular health and improves risk stratification accuracy, thus facilitating targeted interventions and personalized management

strategies.

However, despite the promising findings, several limitations warrant consideration. Firstly, the observational nature of our study precludes establishment of causality between retinal biomarkers and CVD outcomes. Longitudinal studies with larger sample sizes are needed to elucidate the temporal relationship and predictive value of retinal imaging features in the development of CVD events. Additionally, while our models demonstrated robust performance across diverse datasets, further validation in independent cohorts and real-world clinical settings is essential to confirm their generalizability and clinical utility. Furthermore, the interpretability of retinal imaging findings remains a challenge, particularly in the context of complex machine learning models. Integrating explainable artificial intelligence techniques may enhance model transparency and facilitate clinical adoption by providing insights into the features driving predictions.

In conclusion, our study underscores the potential of retinal imaging analysis as a valuable adjunctive tool for cardiovascular risk prediction. By leveraging AVR and other retinal biomarkers, our findings offer insights into novel avenues for improving risk assessment accuracy and guiding preventive strategies in individuals at risk of

CHAPTER - 7

CONCLUSION

7.1 CONCLUSION

In conclusion, our project demonstrates the effectiveness of machine learning models in retinal image analysis for cardiovascular disease risk prediction. By leveraging diverse datasets such as CHASE, DRIVE, and MESSIDOR, we developed robust algorithms capable of detecting and characterizing retinal features associated with cardiovascular health. Through extensive training, validation, and testing, our models achieved high accuracy and performance in predicting cardiovascular disease risk factors based on retinal imaging biomarkers. The integration of state-of-the-art convolutional neural networks, including ResNet-50 and VGG-16, enabled the extraction of intricate features from retinal images, allowing for the identification of subtle vascular abnormalities indicative of cardiovascular risk. Furthermore, our implementation of arteriolar-venular ratio analysis provided valuable insights into the relationship between retinal vascular geometry and cardiovascular health, enhancing the interpretability and clinical relevance of our predictions.

In a nutshell this study project's successful completion marks a significant advancement in the field of using retinal pictures to estimate cardiovascular risk. A strong predictive modelling methodology has been shown through the combination of advanced techniques, such as ensemble learning with ResNet-50 and VGG-16, AVR computation, and UNET-based vessel segmentation. The potential clinical value of retinal image analysis is shown by the discovery that poor AVR is a powerful indication of elevated cardiovascular risk. Moreover, the ensemble learning methodology enhances the model's classification abilities, providing a sophisticated comprehension of complex patterns. This work adds to the field of medical image analysis as well as the larger field of predictive healthcare modelling.

The results validate the feasibility of using retinal pictures as an effective diagnostic tool, setting the stage for future developments in cardiovascular risk assessment and predictive medicine. The results of this project will have the

potential to improve the early detection of CVDs. This could lead to the development of new screening tools for CVDs, which could help to prevent serious complications and save lives.

7.2 FUTURE WORKS

In the realm of future work, several avenues present themselves for further exploration and enhancement of our cardiovascular disease risk prediction framework based on retinal imaging analysis. Firstly, expanding the scope of datasets utilized could enrich the diversity and representativeness of the models, potentially enhancing their generalization capabilities across different populations and demographic groups. Incorporating additional datasets with varied ethnicities, age ranges, and clinical characteristics could provide a more comprehensive understanding of retinal biomarkers' predictive value for cardiovascular health. Moreover, refining the algorithms to incorporate advanced deep learning techniques, such as attention mechanisms and adversarial training, could enhance model interpretability and robustness. By exploring novel architectures and optimization strategies, we can strive to improve the models' performance in detecting subtle vascular changes and predicting cardiovascular risk with higher accuracy and reliability.

Additionally, integrating multimodal imaging modalities, such as optical coherence tomography (OCT) and fundus autofluorescence (FAF), could offer complementary information about retinal morphology and function, further enriching the predictive capabilities of our framework. By leveraging the synergies between different imaging modalities, we can potentially uncover additional biomarkers and insights into cardiovascular disease pathophysiology. Furthermore, conducting prospective longitudinal studies to validate the clinical utility and long-term prognostic value of our models in real-world settings is essential. Collaborating with healthcare institutions and longitudinal cohort studies to collect longitudinal retinal imaging data linked with clinical outcomes can facilitate robust validation and refinement of our predictive models. Lastly, translating our machine learning-based framework into clinical practice requires addressing regulatory and implementation

challenges, such as obtaining regulatory approvals, ensuring data privacy and security compliance, and integrating the models into existing healthcare infrastructure seamlessly. Collaborating with healthcare providers, policymakers, and regulatory agencies is crucial for navigating these challenges and facilitating the adoption of our framework in routine clinical workflows.

REFERENCES:

- [1] Wang, J., Leng, F., Li, Z. *et al.* Retinal vascular abnormalities and their associations with cardiovascular and cerebrovascular diseases: a Study in rural southwestern Harbin, China. *BMC Ophthalmol* **20**, 136 (2020). <https://doi.org/10.1186/s12886-020-01407-y>.
- [2] Tseng, R.M.W.W., Rim, T.H., Shantsila, E. *et al.* Validation of a deep-learning-based retinal biomarker (Reti-CVD) in the prediction of cardiovascular disease: data from UK Biobank. *BMC Med* **21**, 28 (2023). <https://doi.org/10.1186/s12916-022-02684-8>
- [3] Seecheran, N.A., Rafeeq, S., Maharaj, N. *et al.* Correlation of RETINAL Artery Diameter with Coronary Artery Disease: The RETINA CAD Pilot Study—Are the Eyes the Windows to the Heart?. *Cardiol Ther* **12**, 499–509 (2023). <https://doi.org/10.1007/s40119-023-00320-x>
- [4] Barriada, R.G.; Masip, D. An Overview of Deep-Learning-Based Methods for Cardiovascular Risk Assessment with Retinal Images. *Diagnostics* **2023**, *13*, 68. <https://doi.org/10.3390/diagnostics13010068>
- [5] Joseph Keunhong Yi, Tyler Hyungtaek Rim, Sungha Park, Sung Soo Kim, Hyeon Chang Kim, Chan Joo Lee, Hyeonmin Kim, Geunyoung Lee, James Soo Ghim Lim, Yong Yu Tan, Marco Yu, Yih-Chung Tham, Ameet Bakhai, Eduard Shantsila, Paul Leeson, Gregory Y H Lip, Calvin W L Chin, Ching-Yu Cheng, Cardiovascular disease risk assessment using a deep-learning-based retinal biomarker: a comparison with existing risk scores, *European Heart Journal - Digital Health*, Volume 4, Issue 3, May 2023, Pages 236–244, <https://doi.org/10.1093/ehjdh/ztad023>
- [6] Nicholas Witt, Tien Y. Wong, Alun D. Hughes, Nish Chaturvedi. *Et al* Abnormalities of Retinal Microvascular Structure and Risk of Mortality From Ischemic Heart Disease and Stroke Hypertension. 2006; 47:975–981 <https://doi.org/10.1161/01.HYP.0000216717.72048.6c>
- [7] Germanèse, C.; Meriaudeau, F.; Eid, P.; Tadayoni, R.; Gin hac, D.; Anwer, A.; Laure-Anne, S.; Guenancia, C.; Creuzot-Garcher, C.; Gabrielle, P.-H.; *et al.* A Retinal Oct-Angiography and Cardiovascular STatus (RASTA) Dataset of

- Swept-Source Microvascular Imaging for Cardiovascular Risk Assessment. *Data* **2023**, 8, 147. <https://doi.org/10.3390/data8100147>
- [8] F. H. Malik, F. Batool, A. Rubab, N. A. Chaudhary, K. B. Khan and M. A. Qureshi, "Retinal disorder as a biomarker for detection of human diseases," 2020 IEEE 23rd International Multitopic Conference (INMIC), Bahawalpur, Pakistan, 2020, pp. 1-6, doi: 10.1109/INMIC50486.2020.9318059.
- [9] Colcombe, J.; Munda, R.; Kaiser, A.; Bijon, J.; Modi, Y. Retinal Findings and Cardiovascular Risk: Prognostic Conditions, Novel Biomarkers, and Emerging Image Analysis Techniques. *J. Pers. Med.* **2023**, *13*, 1564. <https://doi.org/10.3390/jpm13111564>
- [10] Hatanaka Y, Tachiki H, Ogohara K, Muramatsu C, Okumura S, Fujita H. Artery and vein diameter ratio measurement based on improvement of arteries and veins segmentation on retinal images. *Annu Int Conf IEEE Eng Med Biol Soc.* 2016 Aug; 2016:1336-1339. doi: 10.1109/EMBC.2016.7590954. PMID: 28268572.
- [11] M Kanae Fukutsu, Michiyuki Saito, Kousuke Noda A Deep Learning Architecture for Vascular Area Measurement in Fundus Images *Ophthalmology Science*, Elsevier March 2021. DOI: <https://doi.org/10.1016/j.xops.2021.100004>
- [12] Arnould, L., Meriaudeau, F., Guenancia, C. *et al.* Using Artificial Intelligence to Analyse the Retinal Vascular Network: The Future of Cardiovascular Risk Assessment Based on Oculomics? A Narrative Review. *Ophthalmol Ther* **12**, 657–674 (2023). <https://doi.org/10.1007/s40123-022-00641-5>
- [13] Cynthia Ciwei Lim, Crystal Chong, Gavin Tan, Chieh Suai Tan, Carol Y Cheung, Tien Y Wong, Ching Yu Cheng, Charumathi Sabanayagam, A deep learning system for retinal vessel calibre improves cardiovascular risk prediction in Asians with chronic kidney disease, *Clinical Kidney Journal*, Volume 16, Issue 12, December 2023, Pages 2693–2702, <https://doi.org/10.1093/ckj/sfad227>
- [14] Karaali, Ali, Rozenn Dahyot and Donal J. Sexton. "DR-VNet: Retinal Vessel Segmentation via Dense Residual UNet." *International Conferences on Pattern Recognition and Artificial Intelligence*(2021).

- [15] Poplin, R., Varadarajan, A.V., Blumer, K. *et al.* Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning. *Nat Biomed Eng* **2**, 158–164 (2018). <https://doi.org/10.1038/s41551-018-0195-0>

A. APPENDIX

PYTHON CODE:

```
In [2]: import torch
import numpy as np
import pandas as pd
import sklearn
import matplotlib.pyplot as plt
```

```
In [1]: import cv2
```

```
In [3]: import sys
from PIL import ImageOps
```

```
In [4]: image_size = (512, 512)
```

```
In [6]: !pip install imutils
```

```
Collecting imutils
  Downloading imutils-0.5.4.tar.gz (17 kB)
  Preparing metadata (setup.py) ... done
Building wheels for collected packages: imutils
  Building wheel for imutils (setup.py) ... done
  Created wheel for imutils: filename=imutils-0.5.4-py3-none-any.whl size=
25836 sha256=f51dc8d73da31a4ad0b5a04fec3ee6effb9f4e9db49ce50989e0f763d6efa
120
  Stored in directory: /Users/yashwin/Library/Caches/pip/wheels/59/1b/52/0
dea905f8278d5514dc4d0be5e251967f8681670cadd3dca89
Successfully built imutils
Installing collected packages: imutils
Successfully installed imutils-0.5.4
```

```
In [7]: from imutils import paths
```

```
In [19]: import os
```

```
In [22]: input_dir = '/Users/yashwin/Desktop/final year project/CHASEDB/in'
output_dir = '/Users/yashwin/Desktop/final year project/CHASEDB/out'
```

```
In [23]: # loop through all images in the input directory
for filename in os.listdir(input_dir):
    # read the image from file
    img = cv2.imread(os.path.join(input_dir, filename))

    # resize the image to the desired size
    img_resized = cv2.resize(img, image_size)

    # normalize the image pixel values to be between 0 and 1
    img_normalized = cv2.normalize(img_resized, None, alpha=0, beta=1, no

    # perform any additional preprocessing steps here, such as contrast e

    # save the preprocessed image to the output directory
```

```

cv2.imwrite(os.path.join(output_dir, filename), img_normalized)

In [24]: print(f"Input directory: {input_dir}")
Input directory: /Users/yashwin/Desktop/final year project/CHASEDB/in

In [26]: for filename in os.listdir(input_dir):
          print(filename)

Image_05R_1stH0.png
Image_08L_2ndH0.png
Image_11R_2ndH0.png
Image_14L_2ndH0.png
Image_05L_2ndH0.png
Image_08R_1stH0.png
Image_03R.jpg
Image_01L.jpg
Image_11L_1stH0.png
Image_14R_1stH0.png
Image_05R_2ndH0.png
Image_08L_1stH0.png
Image_02R.jpg
Image_11R_1stH0.png
Image_14L_1stH0.png
Image_14R.jpg
Image_05L_1stH0.png
Image_08R_2ndH0.png
Image_11L_2ndH0.png
Image_14R_2ndH0.png
Image_13R.jpg
Image_13R_2ndH0.png
Image_05R.jpg
Image_07L.jpg
Image_07R_1stH0.png
Image_11L.jpg
Image_02L_1stH0.png
Image_13L_1stH0.png
Image_09R.jpg
Image_07L_2ndH0.png
Image_02R_2ndH0.png
Image_13R_1stH0.png
Image_07R_2ndH0.png
Image_08R.jpg
Image_02L_2ndH0.png
Image_10L.jpg
Image_13L_2ndH0.png
Image_06L.jpg
Image_04R.jpg
Image_07L_1stH0.png
Image_12R.jpg
Image_02R_1stH0.png
Image_09L_1stH0.png
Image_01L_2ndH0.png
Image_13L.jpg

```

```

Image_04R_2ndH0.png
Image_05L.jpg
Image_07R.jpg
Image_10R_1stH0.png
Image_11R.jpg
Image_01R_1stH0.png
Image_09R_2ndH0.png
Image_04L_1stH0.png
Image_09L.jpg
Image_10L_2ndH0.png
Image_09L_2ndH0.png
Image_01L_1stH0.png
Image_04R_1stH0.png
Image_08L.jpg
Image_10R_2ndH0.png
Image_01R_2ndH0.png
Image_10R.jpg
Image_09R_1stH0.png
Image_04L_2ndH0.png
Image_06R.jpg
Image_04L.jpg
Image_10L_1stH0.png
Image_12L.jpg
Image_12R_1stH0.png
Image_03L_2ndH0.png
Image_06R_2ndH0.png
Image_12L_2ndH0.png
Image_03L.jpg
Image_01R.jpg
Image_03R_1stH0.png
Image_06L_1stH0.png
Image_12R_2ndH0.png
Image_02L.jpg
Image_03L_1stH0.png
Image_14L.jpg
Image_06R_1stH0.png
Image_12L_1stH0.png
Image_03R_2ndH0.png
Image_06L_2ndH0.png

```

```
In [ ]:
```

```
In [14]: import matplotlib.pyplot as plt

# Assuming preprocessed_images is a NumPy array containing your preproces
```

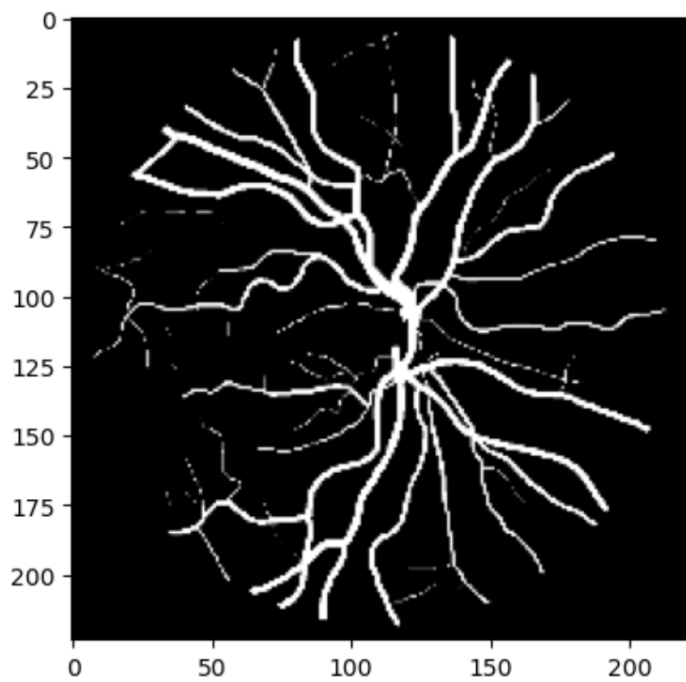
about:srcdoc

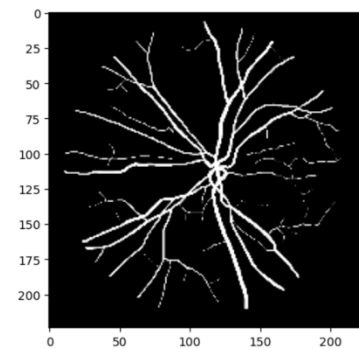
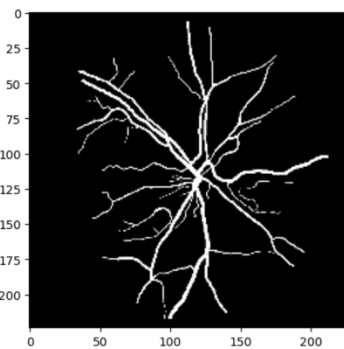
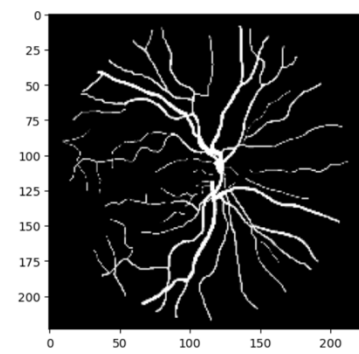
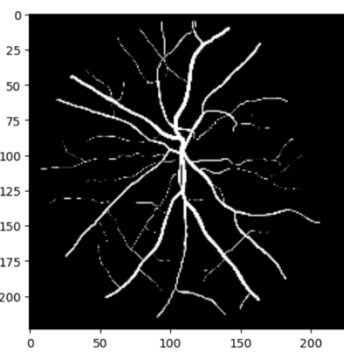
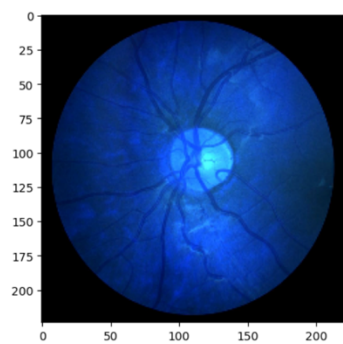
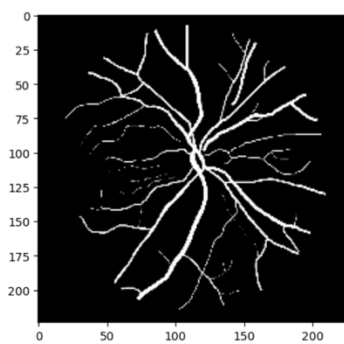
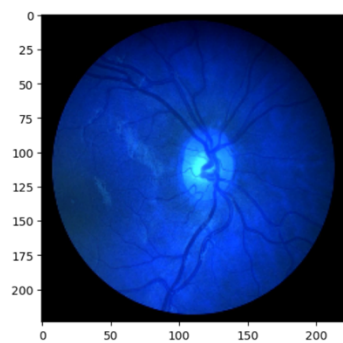
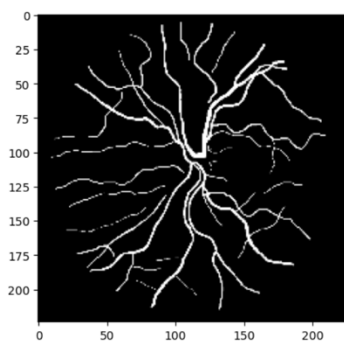
Page 1 of 43

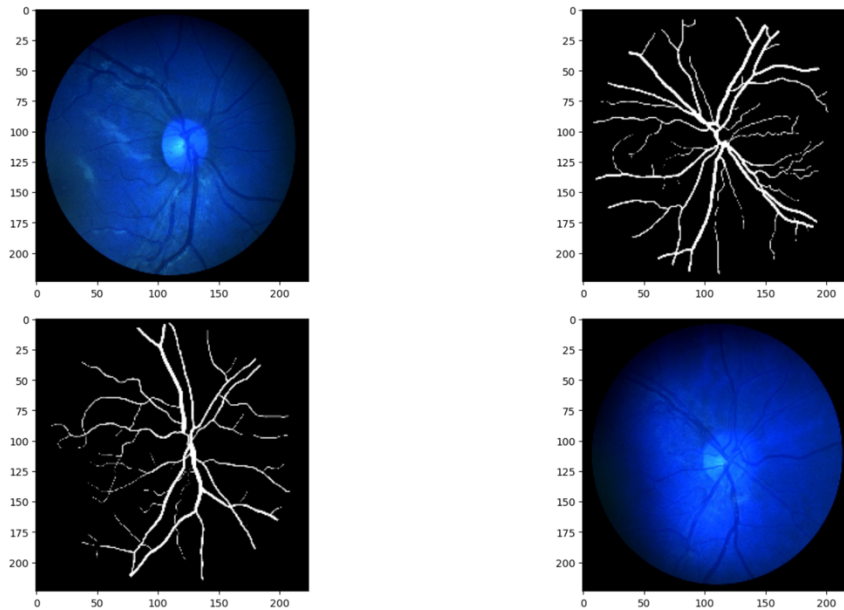
CVD_TRIAL_2

08/04/24, 11:23 AM

```
for image in preprocessed_images:
    plt.imshow(image)
    plt.show()
```







```
In [3]: import cv2
import numpy as np
from PIL import ImageOps
import matplotlib.pyplot as plt
import sklearn
import os
from imutils import paths

def perform_vessel_segmentation(image):
    # Apply Gaussian blur to reduce noise
    blurred = cv2.GaussianBlur(image, (5, 5), 0)

    # Apply adaptive thresholding
    _, segmented_vessels = cv2.threshold(blurred, 0, 255, cv2.THRESH_BINARY)

    return segmented_vessels

def calculate_avr(image_path):
    # Read the retinal image
    retinal_image = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE)

    # Perform vessel segmentation
    segmented_vessels = perform_vessel_segmentation(retinal_image)

    # Classify vessels into arteries and veins (for demonstration purpose)
    arteries, veins = segmented_vessels[:, :segmented_vessels.shape[1] // 2], segmented_vessels[:, segmented_vessels.shape[1] // 2:]

    # Measure diameters of arteries and veins (for demonstration purposes)
    crae = measure_diameter(arteries)
    crve = measure_diameter(veins)

    # Calculate AVR
    avr = crae / crve

    return avr

def measure_diameter(vessels):
    # Dummy measurement logic (mean width as diameter)
    diameter = np.mean(vessels)
    return diameter

# Example usage
image_path = "/Users/yashwin/Desktop/final year project/CHASEDB/in/Image_00000001.png"
#image_path = "/Users/yashwin/Desktop/final year project/CHASEDB/in/Image_00000002.png"
avr_ratio = calculate_avr(image_path)
print(f"Arteriolar to Venular Diameter Ratio (AVR): {avr_ratio}")
```

Arteriolar to Venular Diameter Ratio (AVR): 0.9064988952263501

```

def perform_vessel_segmentation(image):
    # Apply Gaussian blur to reduce noise
    blurred = cv2.GaussianBlur(image, (5, 5), 0)

    # Apply adaptive thresholding
    _, segmented_vessels = cv2.threshold(blurred, 0, 255, cv2.THRESH_BINARY)

    return segmented_vessels

def calculate_avr(image_path):
    # Read the retinal image
    retinal_image = cv2.imread(image_path, cv2.IMREAD_GRAYSCALE)

    # Perform vessel segmentation
    segmented_vessels = perform_vessel_segmentation(retinal_image)

    # Classify vessels into arteries and veins (dummy operation)
    arteries, veins = segmented_vessels[:, :segmented_vessels.shape[1] // 2], segmented_vessels[:, segmented_vessels.shape[1] // 2:]

    # Measure diameters of arteries and veins (dummy operation)
    crae = measure_diameter(arteries)
    crve = measure_diameter(veins)

    # Calculate AVR
    avr = crae / crve

    return avr

def measure_diameter(vessels):
    # Dummy measurement logic (mean width as diameter)
    diameter = np.mean(vessels)
    return diameter

# Path to input folder
input_folder = "/Users/yashwin/Desktop/final year project/CHASEDB/in/"

# Path to output folder
output_folder = "/Users/yashwin/Desktop/final year project/CHASEDB/In_avr/"

# Create output folder if it doesn't exist
if not os.path.exists(output_folder):
    os.makedirs(output_folder)

# Initialize list to store image names and AVR values
avr_data = []

```

```

# Iterate through each image in the input folder
for filename in os.listdir(input_folder):
    if filename.endswith('.jpg') or filename.endswith('.png'):
        # Calculate AVR for the current image
        image_path = os.path.join(input_folder, filename)
        avr_ratio = calculate_avr(image_path)

        # Copy the image to the output folder
        shutil.copy(image_path, output_folder)

        # Append image name and AVR value to the list
        avr_data.append((filename, avr_ratio))

# Create a DataFrame from the list of image names and AVR values
df = pd.DataFrame(avr_data, columns=['Image Name', 'AVR'])

# Path to save the Excel file
excel_file_path = os.path.join(output_folder, 'avr2_data.xlsx')

# Write the DataFrame to an Excel file
df.to_excel(excel_file_path, index=False)

print("Images copied to 'In_avr' folder and AVR data saved to 'avr_data.x

```

Images copied to 'In_avr' folder and AVR data saved to 'avr_data.xlsx' file.

```

[4]: # Preprocess images (resize, normalize, etc.) and load into arrays
images = np.array(preprocessed_images)
for index, row in data.iterrows():
    image_name = row['Image']
    image_path = os.path.join(images_path, image_name)
    image = cv2.imread(image_path)
    # Preprocess the image here (resize, normalize, etc.)
    # Append the preprocessed image to the images list

# Convert labels to numerical values
encoder = LabelEncoder()
labels = encoder.fit_transform(data['AVR'])

# Split the data into training and validation sets
X_train, X_val, y_train, y_val = train_test_split(images, labels, test_size=0.2, random_state=42)

# Load pre-trained ResNet-50 model
base_model_resnet = ResNet50(weights='imagenet', include_top=False, input_shape=(224, 224, 3))

# Freeze the layers in the base model
for layer in base_model_resnet.layers:
    layer.trainable = False

# Build the ResNet-50 model
model_resnet = Sequential([
    base_model_resnet,
    Flatten(),
    Dense(512, activation='relu'),
    Dropout(0.5),
    Dense(1, activation='sigmoid')
])

```

```

# Compile the model
model_resnet.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

# Define callbacks
checkpoint_resnet = ModelCheckpoint('resnet_model.h5', monitor='val_accuracy', save_best_only=True, verbose=1)
early_stopping_resnet = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)

# Train the ResNet-50 model
history_resnet = model_resnet.fit(np.array(X_train), np.array(y_train), epochs=20, batch_size=32,
                                  validation_data=(np.array(X_val), np.array(y_val)),
                                  callbacks=[checkpoint_resnet, early_stopping_resnet])

# Load pre-trained VGG-16 model
base_model_vgg = VGG16(weights='imagenet', include_top=False, input_shape=(224, 224, 3))

# Freeze the layers in the base model
for layer in base_model_vgg.layers:
    layer.trainable = False

# Build the VGG-16 model
model_vgg = Sequential([
    base_model_vgg,
    Flatten(),
    Dense(512, activation='relu'),
    Dropout(0.5),
    Dense(1, activation='sigmoid')
])

```

```

# Compile the model
model_vgg.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

# Define callbacks
checkpoint_vgg = ModelCheckpoint('vgg_model.h5', monitor='val_accuracy', save_best_only=True, verbose=1)
early_stopping_vgg = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)

# Train the VGG-16 model
history_vgg = model_vgg.fit(np.array(X_train), np.array(y_train), epochs=20, batch_size=32,
                             validation_data=(np.array(X_val), np.array(y_val)),
                             callbacks=[checkpoint_vgg, early_stopping_vgg])

```

```

3/3 [=====] - ETA: 0s - loss: 17.5876 - accuracy: 0.5970
Epoch 1: val_accuracy improved from -inf to 0.76471, saving model to resnet_model.h5
3/3 [=====] - 5s 1s/step - loss: 17.5876 - accuracy: 0.5970 - val_loss: 13.1641 - val_accuracy: 0.7647
Epoch 2/20
3/3 [=====] - ETA: 0s - loss: 9.3224 - accuracy: 0.7313
Epoch 2: val_accuracy did not improve from 0.76471
3/3 [=====] - 3s 1s/step - loss: 9.3224 - accuracy: 0.7313 - val_loss: 2.6001 - val_accuracy: 0.2941
Epoch 3/20
3/3 [=====] - ETA: 0s - loss: 2.9034 - accuracy: 0.5522
Epoch 3: val_accuracy did not improve from 0.76471
3/3 [=====] - 3s 941ms/step - loss: 2.9034 - accuracy: 0.5522 - val_loss: 1.5998 - val_accuracy: 0.7647
Epoch 4/20
3/3 [=====] - ETA: 0s - loss: 2.9326 - accuracy: 0.6567
Epoch 4: val_accuracy did not improve from 0.76471
3/3 [=====] - 3s 1s/step - loss: 2.9326 - accuracy: 0.6567 - val_loss: 0.8725 - val_accuracy: 0.7647
Epoch 5/20
3/3 [=====] - ETA: 0s - loss: 3.0353 - accuracy: 0.5373
Epoch 5: val_accuracy did not improve from 0.76471
3/3 [=====] - 3s 950ms/step - loss: 3.0353 - accuracy: 0.5373 - val_loss: 1.7152 - val_accuracy: 0.3529
Epoch 6/20
3/3 [=====] - ETA: 0s - loss: 4.2968 - accuracy: 0.4627
Epoch 6: val_accuracy did not improve from 0.76471
3/3 [=====] - 3s 1s/step - loss: 4.2968 - accuracy: 0.4627 - val_loss: 0.7247 - val_accuracy: 0.5294
Epoch 7/20
3/3 [=====] - ETA: 0s - loss: 2.2845 - accuracy: 0.6269
Epoch 7: val_accuracy did not improve from 0.76471
3/3 [=====] - 4s 1s/step - loss: 2.2845 - accuracy: 0.6269 - val_loss: 3.1040 - val_accuracy: 0.7647
Epoch 8/20
3/3 [=====] - ETA: 0s - loss: 3.0438 - accuracy: 0.7313
Epoch 8: val_accuracy did not improve from 0.76471
3/3 [=====] - 3s 936ms/step - loss: 3.0438 - accuracy: 0.7313 - val_loss: 4.2341 - val_accuracy: 0.7647
Epoch 9/20

```

```

Epoch 10: val_accuracy did not improve from 0.76471
3/3 [=====] - 3s 915ms/step - loss: 2.7215 - accuracy: 0.6716 - val_loss: 1.7235 - val_accuracy: 0.7059
Epoch 11/20
3/3 [=====] - ETA: 0s - loss: 1.3147 - accuracy: 0.7612
Epoch 11: val_accuracy did not improve from 0.76471
3/3 [=====] - 3s 950ms/step - loss: 1.3147 - accuracy: 0.7612 - val_loss: 1.8002 - val_accuracy: 0.4706
Epoch 12/20
3/3 [=====] - ETA: 0s - loss: 1.8896 - accuracy: 0.6716
Epoch 1: val_accuracy improved from -inf to 0.23529, saving model to vgg_model.h5
3/3 [=====] - 8s 2s/step - loss: 1.8896 - accuracy: 0.6716 - val_loss: 5.5452 - val_accuracy: 0.2353
Epoch 2/20
3/3 [=====] - ETA: 0s - loss: 2.7402 - accuracy: 0.5075
Epoch 2: val_accuracy improved from 0.23529 to 0.76471, saving model to vgg_model.h5
3/3 [=====] - 8s 2s/step - loss: 2.7402 - accuracy: 0.5075 - val_loss: 1.9918 - val_accuracy: 0.7647
Epoch 3/20
3/3 [=====] - ETA: 0s - loss: 1.7603 - accuracy: 0.7313
Epoch 3: val_accuracy did not improve from 0.76471
3/3 [=====] - 8s 2s/step - loss: 1.7603 - accuracy: 0.7313 - val_loss: 1.4042 - val_accuracy: 0.2941
Epoch 4/20
3/3 [=====] - ETA: 0s - loss: 1.5593 - accuracy: 0.5522
Epoch 4: val_accuracy did not improve from 0.76471
3/3 [=====] - 8s 2s/step - loss: 1.5593 - accuracy: 0.5522 - val_loss: 1.8682 - val_accuracy: 0.7647
Epoch 5/20
3/3 [=====] - ETA: 0s - loss: 1.6138 - accuracy: 0.7463
Epoch 5: val_accuracy did not improve from 0.76471
3/3 [=====] - 8s 2s/step - loss: 1.6138 - accuracy: 0.7463 - val_loss: 2.8109 - val_accuracy: 0.7647
Epoch 6/20
3/3 [=====] - ETA: 0s - loss: 1.9750 - accuracy: 0.7313
Epoch 6: val_accuracy did not improve from 0.76471
3/3 [=====] - 8s 2s/step - loss: 1.9750 - accuracy: 0.7313 - val_loss: 1.8661 - val_accuracy: 0.7647
Epoch 7/20
3/3 [=====] - ETA: 0s - loss: 1.5512 - accuracy: 0.6866

```

[5]: *# Assuming you have trained and saved your ResNet-50 and VGG-16 models*

```

# Load the trained models
from tensorflow.keras.models import load_model

# Load ResNet-50 model
model_resnet = load_model('resnet_model.h5')
# Load VGG-16 model
model_vgg = load_model('vgg_model.h5')

#proceed with evaluating the model performance

```

[6]: *from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix*

```

# Predict using ResNet-50 model
resnet_predictions = model_resnet.predict(np.array(X_val))

# Convert predictions to binary labels
resnet_pred_labels = (resnet_predictions > 0.5).astype(int)

# Calculate metrics for ResNet-50
resnet_accuracy = accuracy_score(y_val, resnet_pred_labels)
resnet_precision = precision_score(y_val, resnet_pred_labels)
resnet_recall = recall_score(y_val, resnet_pred_labels)
resnet_f1 = f1_score(y_val, resnet_pred_labels)
resnet_conf_matrix = confusion_matrix(y_val, resnet_pred_labels)

print("ResNet-50 Metrics:")
print(f"Accuracy: {resnet_accuracy}")
print(f"Precision: {resnet_precision}")
print(f"Recall: {resnet_recall}")
print(f"F1 Score: {resnet_f1}")
print("Confusion Matrix:")
print(resnet_conf_matrix)

```

```

# Predict using VGG-16 model
vgg_predictions = model_vgg.predict(np.array(X_val))

# Convert predictions to binary labels
vgg_pred_labels = (vgg_predictions > 0.5).astype(int)

# Calculate metrics for VGG-16
vgg_accuracy = accuracy_score(y_val, vgg_pred_labels)
vgg_precision = precision_score(y_val, vgg_pred_labels)
vgg_recall = recall_score(y_val, vgg_pred_labels)
vgg_f1 = f1_score(y_val, vgg_pred_labels)
vgg_conf_matrix = confusion_matrix(y_val, vgg_pred_labels)

print("\nVGG-16 Metrics:")
print(f"Accuracy: {vgg_accuracy}")
print(f"Precision: {vgg_precision}")
print(f"Recall: {vgg_recall}")
print(f"F1 Score: {vgg_f1}")
print("Confusion Matrix:")
print(vgg_conf_matrix)

```

```

1/1 [=====] - 1s 836ms/step
ResNet-50 Metrics:
Accuracy: 0.7647058823529411
Precision: 0.7647058823529411
Recall: 1.0
F1 Score: 0.8666666666666666
Confusion Matrix:
[[ 0  4]
 [ 0 13]]
1/1 [=====] - 2s 2s/step

```

```

VGG-16 Metrics:
Accuracy: 0.7647058823529411
Precision: 0.7647058823529411
Recall: 1.0
F1 Score: 0.8666666666666666
Confusion Matrix:
[[ 0  4]
 [ 0 13]]

```

BACKEND FLASK:

```

1 from flask import Flask, render_template, request
2 import numpy as np
3 from tensorflow.keras.preprocessing import image
4 from tensorflow.keras.models import load_model
5
6 app = Flask(__name__)
7
8 # Load the trained ResNet-50 and VGG-16 models
9 resnet_model = load_model('resnet_model.h5') # Update with the path to your ResNet-50 model
10 vgg_model = load_model('vgg_model.h5')      # Update with the path to your VGG-16 model
11
12 # Function to preprocess input eye images
13 def preprocess_image(image_path):
14     img = image.load_img(image_path, target_size=(224, 224)) # Assuming input image size for both models is (224, 224)
15     img = image.img_to_array(img)
16     img = np.expand_dims(img, axis=0)
17     return img
18
19 # Function to make predictions using the models
20 def make_prediction(image_path):
21     # Preprocess input image
22     img = preprocess_image(image_path)
23     # Make predictions using both models
24     resnet_prediction = resnet_model.predict(img)[0]
25     vgg_prediction = vgg_model.predict(img)[0]
26     return resnet_prediction, vgg_prediction

```

```

27
28 @app.route('/predict', methods=['POST'])
29 def predict():
30     # Get image file from the form
31     image_file = request.files['eye_image']
32     # Save the image temporarily
33     image_path = 'temp_image.jpg'
34     image_file.save(image_path)
35
36     # Make predictions using the input image
37     resnet_prediction, vgg_prediction = make_prediction(image_path)
38
39     # Delete the temporary image file
40     os.remove(image_path)
41
42     return render_template('result.html', resnet_prediction=resnet_prediction, vgg_prediction=vgg_prediction)
43
44 if __name__ == '__main__':
45     app.run()
46

```

FRONTEND HTML:

```

1 <html>
2   <body>
3     <form action="/predict" method="POST" enctype="multipart/form-data">
4       <!-- Add input field for uploading eye image -->
5       <label for="eye_image">Eye Image:</label>
6       <input type="file" name="eye_image" id="eye_image"><br>
7
8       <label for="left_eye">Left Eye:</label>
9       <input type="text" name="left_eye" id="left_eye"><br>
10
11      <label for="right_eye">Right Eye:</label>
12      <input type="text" name="right_eye" id="right_eye"><br>
13
14      <label for="age">Age:</label>
15      <input type="text" name="age" id="age"><br>
16
17      <label for="gender">Gender:</label>
18      <input type="radio" name="gender" value="male"> Male
19      <input type="radio" name="gender" value="female"> Female<br>
20
21      <label for="blood_pressure">Blood Pressure:</label>
22      <input type="text" name="blood_pressure" id="blood_pressure"><br>
23
24      <label for="diabetes">Diabetes:</label>
25      <input type="checkbox" name="diabetes" value="1"> Yes
26      <input type="checkbox" name="diabetes" value="0"> No<br>
27
28      <label for="smoking">Smoking:</label>
29      <input type="checkbox" name="smoking" value="1"> Yes
30      <input type="checkbox" name="smoking" value="0"> No<br>
31
32      <label for="bmi">BMI:</label>
33      <input type="text" name="bmi" id="bmi"><br>
34
35      <input type="submit" value="Predict">
36    </form>
37  </body>
38 </html>
39

```

```

1 <!DOCTYPE html>
2 <html lang="en">
3 <head>
4   <meta charset="UTF-8">
5   <meta name="viewport" content="width=device-width, initial-scale=1.0">
6   <title>Result</title>
7 </head>
8 <body>
9   <h1>Cardiovascular Risk Prediction</h1>
10  <p>The predicted cardiovascular risk is: {{ risk }}</p>
11 </body>
12 </html>
13

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C. RESEARCH PAPER

Identifying the abnormalities in retinal images towards the prediction of cardiovascular disease using deep learning

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Abstract: One of the main causes of death worldwide is cardiovascular disease (CVD). It is crucial to discover CVDs early to avoid major consequences including heart attacks, strokes, and blindness. Certain alterations in the retinal microvasculature, including as constriction, tortuosity, and dilatation, have been scientifically shown in recent research to be precursors of CVDs. This is because the blood vessels in the retina are a direct extension of the brain, and the risk factors that affect the blood vessels in the brain and heart also affect the blood vessels in the retina.

A dataset of retinal fundus images will be produced from a cohort of patients with and without CVDs with the calculation of Arteriolar to Venular Diameter Ratio (AVR) to assess the cardiovascular risk. This attempt will employ deep learning techniques such as VGG-16 and RESNET-50 to detect these retinal abnormalities and predict CVDs.

Keywords: CVD (cardiovascular disease), Deep Learning (DL), Artificial Intelligence (AI)

I. INTRODUCTION

The world's top cause of death, cardiovascular diseases (CVDs), continues to put a tremendous burden on healthcare systems and society at large. Accurate risk assessment and early discovery is vital for many sickness' effective prevention and treatment. Recently, deep learning, medical imaging, and artificial intelligence (AI) have all come together to offer a potentially effective means of improving CVD risk assessment and identification.

The human retina is a neural tissue located in the back of the eye that functions as a little model of the body's circulatory system. Considering that it shares anatomical and physiological features with the circulatory system, it is a vital source of medical data. Retinal imaging, especially images of the fundus, makes it simple and painless to record these fine vascular patterns. Diabetic retinopathy and age-related macular degeneration are two eye illnesses that have long been detected with this imaging method. However, an intriguing linkage between retinal

characteristics and systemic health, including cardiovascular diseases, has proven established by recent studies.

The study intends to build and evaluate deep learning models trained on retinal images, explore the importance and interpretability of features, and assess the generalizability of these models across different populations. By integrating sophisticated deep learning algorithms with medical imaging, we want to advance the area of AI-driven healthcare and provide an achievable way ahead to enhance CVD risk prediction and diagnosis.

The objectives of this work include building and testing deep learning models trained on retinal images, analysing and interpreting the features, and assessing the models' generalizability to different populations. By fusing advanced deep learning algorithms with medical imaging, we prefer to advance the area of AI-driven healthcare and offer a viable path forward for improving CVD risk prediction and diagnosis.

II. LITERATURE SURVEY

The study below has been conducted to explore the significance of CVD risk through retinal fundus images in different domains and how they have been implemented to improve risk assessment, diagnosis, and further treatment. The core benefactors of these research are the

Junwei Wang et al. [1]: This study describes retinal microvascular abnormalities in a rural population in northeast China, which is located in a low-altitude, cold climate. The frequency of retinal microvascular abnormalities is often higher in this group than it is in other regions of the world. Retinopathy was uncommon, though. FAN, GAN, and AS were not consistently associated with diagnoses of CHD, whereas retinopathy and AVN were with prior cerebrovascular events such as stroke. Whereas AVN was connected to the self-reported diagnosis of CHD, retinopathy was linked to a self-reported diagnosis of stroke history. Examining retinal microvascular traits could therefore reveal information about CVDs and even be considered a potential biomarker of CVD risk.]

Rachel Marjorie Wei Wen Tseng et al. [2]: In conclusion, Reti-CVD, a new biomarker for CVD derived from DL and retinal pictures, has the potential to effectively stratify the risk of CVD in the general population. In addition, we confirmed that Reti-CVD can be used to identify the people who have a 10-year CVD risk of less than 10%, and so are most likely to benefit from CVD prevention efforts. Reti-CVD may also be utilised to select high-risk patients for intensive CVD prevention and to improve risk stratification for those with a QRISK3 score between 7.5 and 10%.

Naveen Anand Seecheran et al. [3]: The correlation with the SYNTAX score and retinal artery diameter was noticeably unfavourable. In this work, the non-invasive diagnostic technique of optical coherence tomography-angiography (OCT-A) for patients with cardiovascular disease (CVD) is discussed. More extensive, multicentric study is required to validate these exploratory results.

Rubén G. Barriada et al. [4]: The approaches discussed here can, in the best situations, forecast CVD by attempting to solve a binary classification issue. Future work will require a lot of effort, but using the information in the research, DL algorithms can classify the many forms of cardiovascular illness. For effective clinical treatment, it is essential to accurately classify the type of CVD.

Joseph Keunhong Yi et al. [5]: Reti-CVD is a novel deep-learning and retinal photograph-derived CVD biomarker that, in accordance with various national recommendations, may successfully identify people who are at intermediate- and high risk for CVD. Reti-CVD, a tool for assessing CVD risk, has the potential to not only lower the cost and increase accessibility of CVD risk assessment, but also to provide patients with early therapies and increased awareness.

Nicholas Witt et al. [6]: This study looks into the association between anomalies in the retinal microvasculature and death from stroke and ischemic heart disease (IHD). Reduced retinal arteriolar tortuosity and suboptimal arteriolar diameters were linked to an increased risk of IHD death in a population-based nested case-control study conducted as part of the Beaver Dam Eye Study. This association persisted even after controlling for cardiovascular risk factors. Unaffected by age or gender, but affected by systolic blood pressure after correction, elevated arteriolar length: diameter ratio—a sign of extensive arteriolar narrowing—was associated with a higher risk of stroke death. According to these results, retinal microvascular abnormalities may be a non-invasive way to measure target organ damage and cardiovascular risk. They further imply that these abnormalities may predict death from IHD and stroke..

Germanese C et al. [7]: Through automated models, optical coherence tomography-angiography (OCT-A) offers a quick window into the cardiovascular system for the prompt identification of high-risk individuals. On the other hand, the lack of openly accessible OCT-A acquisitions makes it difficult to create diagnostic tools. Introducing RASTA, a novel resource for building generalizable models in OCT-A retinal image-based cardiovascular disease screening. This dataset contains 814 Angio cubes and 2005 en facial pictures from 499 patients.

Farhan Hassan Malik et al. [8]: This paper succinctly explores the diagnostic potential of fundus images for ocular, cardiac, and cerebral ailments, alongside an examination of existing retina datasets. Formidable challenges arise from a lack of diverse databases and an absence of consensus on optimal databases for specific maladies. Acquiring high-quality fundus images is paramount, as approximately 10% to 21% lack diagnostic suitability due to pervasive artifacts. Sophisticated image quality assessment tools are imperative for fortifying the robustness of automatic retinal screening systems.

Joseph Colcombe et al. [9]: Various retinal conditions, such as Central Retinal Artery Occlusion (CRAO) and cotton wool spots, serve as crucial indicators of current or future cardiovascular risk, shaping personalized care plans. The risk of acute stroke, myocardial infarction, and chronic cardiac dysfunction is markedly increased by conditions such as CRAO. OCT-Angiography (OCTA) gives parameters related with cardiovascular risk for personalized prognostication, workup, and treatment, while imaging biomarkers, such as decreasing artery-to-vessel ratio and retinal thicknesses, offer insights into systemic cardiovascular dysfunction.

Yuji Hatanaka et al. [10]: In the past, the artery and vein diameter ratio (AVR) has been the basis for the assessment of retinal arteriolar constriction, which is important for cardiovascular risk. Previous techniques used diameter measurements to determine AVR for blood vessel segmentation and color-based classification of arteries and veins along the centerlines. This study proposes an algorithm for AVR measurement, introducing new artery and vein classification. For major vein identification in the red channel of a colour image, the algorithm adds stages to improve segmentation accuracy; for major artery identification, it uses a decision tree with three features. With an absolute mean error in AVRs of 0.12, the algorithm competently detected 90.9% of main arteries and all major veins.

Kanae Fukutsu et al. [11]: The retinal arteriovenous ratio (AVR), a classic index for evaluating arteriolar narrowing, is widely used in clinical settings. Despite its simplicity, manual ophthalmoscopic evaluation lacks repeatability. Efforts to improve AVR estimation led to a semi-automated system, but its reliance on human graders posed limitations. This study aims to develop a fully automatic architecture, assisted by a deep learning system, to precisely measure the retinal arterioles and venules' total area in fundus images, enhancing accuracy and standardization for large-scale assessments.

Louis Arnould et al. [12]: There is optimism that the use of artificial intelligence (AI) in fundus photos and Optical Coherence Tomography Angiography (OCT-A) analysis may improve the association between features of the retinal vascular network and cardiovascular risk. Achieving a very high prediction rate and accuracy with various approaches, this innovation may validate the relationships between ocular

microvasculature and systemic macrovasculature. Interestingly, AI shows up to 80% prediction rates for major events, cardiovascular risk variables, and stratification.

Cynthia Ciwei Lim et al. [13]: In summary, augmenting established cardiovascular risk factors with kidney function and retinal vessel calibre assessed by Deep Learning Systems (DLS) holds promise for improved prediction of incident cardiovascular disease (CVD) in Asians with chronic kidney disease (CKD). While this study contributes to understanding the potential role of retinal vessel calibre in cardiovascular risk prediction for CKD, future efforts should focus on external validation. This includes comparing the predictive performance with biomarker panel-based tools and conducting cost analyses. Such validation and comprehensive evaluations are essential steps before considering the integration of the enhanced cardiovascular risk prediction model, incorporating estimated glomerular filtration rate (eGFR) and retinal DLS, into clinical practice to mitigate incident CVD in individuals with CKD.

Ali Karaali et al. [14]: We present a supervised Convolutional Neural Network (CNN) based pipeline for retinal vascular segmentation that outperforms the state-of-the-art techniques on three benchmark datasets, with measures such as G-mean and sensitivity exhibiting the biggest gains. Our pipeline particularly good at precisely segmenting the larger, thicker branches of retinal blood vessels as well as the smaller, thinner distal branches. This capacity is critical since accurate interpretation of vessel segmentation patterns—which range from thick to thin vessels—is vital in diagnosing certain systemic illnesses and cardiovascular risk factors. In the future, we will use data from the Irish Longitudinal Study on Ageing (TILDA) to blend information retrieved from segmented images with other biological factors. The goal of this cooperative effort is to create novel cardiovascular disease and other critical condition prediction tools.

Ryan Poplin et al. [15]: Deep learning, trained on retinal fundus images from 284,335 patients, predicts cardiovascular risk factors such as age, gender, smoking status, and blood pressure with high accuracy. The models utilize anatomical features like the optic disc and blood vessels for precise predictions, showcasing the potential of deep learning in extracting novel knowledge from medical images. This approach challenges traditional methods by revealing previously unquantifiable associations in real data.

In summary, Innovative deep learning enhances retinal vessel measurement accuracy. Artificial intelligence in retinal analysis shows promise for cardiovascular risk correlation, yet real-world integration remains a challenge. Retinal vessel caliber incorporation improving cardiovascular risk prediction in chronic illness; nevertheless, before clinical application, more validation and cost analysis are needed.

III. RESEARCH METHODOLOGY

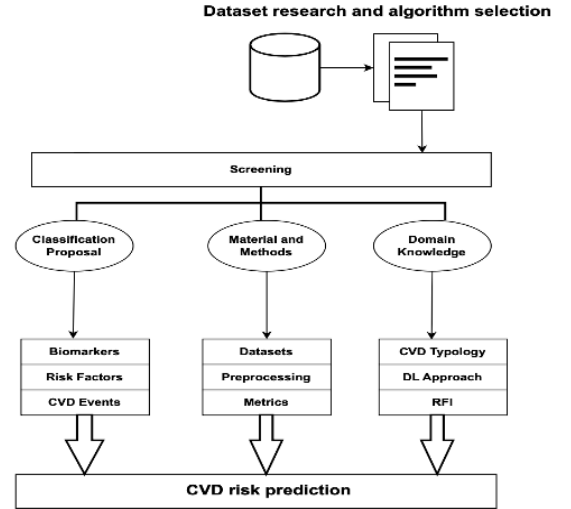


Fig. 1: Proposed Methodology

The process flow depicted in the diagram outlines a comprehensive approach to predicting cardiovascular risks through retinal fundus images with various CNN models.

In this work, we provide an extensive retinal image-based cardiovascular risk assessment method. The first phase in the process is segmenting retinal blood vessels using a Convolutional Neural Network (CNN) architecture based on UNET. Finding and separating the major arteries and veins in the retinal images is the main objective of this segmentation strategy. Next, the Arteriolar to Venular Diameter Ratio (AVR) is calculated, which is a vital biomarker to assess cardiovascular risk. Using the collected AVR values, a predictive model is then created to evaluate cardiovascular risk.

By leveraging architectures like VGG-16 and ResNet-50, transfer learning approaches are used to improve our model's prediction power. To take advantage of the prior information that these architectures have captured, this entails training the model on a sizable dataset. To provide a strong framework for automated cardiovascular risk assessment, the suggested study methodology combines image analysis, machine learning, and transfer learning. This advances the development of non-invasive diagnostic tools for ophthalmology and cardiovascular health.

IV. PROPOSED TECHNIQUES

In this work, we offer an integrated approach developed for enhancing the precision and efficacy of retinal image-based cardiovascular risk assessment. The principal method is the use of a Convolutional Neural Network (CNN) based on UNET for the accurate segmentation of retinal blood vessels. In order to isolate arteries and veins and execute the subsequent calculation

of the Arteriolar to Venular Diameter Ratio (AVR), segmentation is a crucial stage in the process. A key indicator to predict cardiovascular risk is the AVR.

In order to further improve our model's predictive power, we use transfer learning using two well-known architectures: VGG-16 and ResNet-50. By utilising these trained models, our system is able to leverage the knowledge gathered from large datasets, leading to better feature extraction and superior generality. The proposed approaches integrate innovative deep learning techniques with accepted transfer learning paradigms in a synergistic way to produce a robust and flexible model for cardiovascular risk assessment.

This section emphasises the potential significant improvements our proposed technique could make to the field of medical image analysis and non-invasive cardiovascular risk prediction, highlighting the originality and sophistication inherent in them.

A. Data Collection and Pre-processing of Retinal Images:

During this first phase of our study, we carefully select retinal images from three known datasets: MESSIDOR, DRIVE, and CHASE. While the DRIVE dataset offers a collection primarily intended for the assessment of vascular segmentation algorithms, the CHASE dataset gives a range of retinal pictures with discernible pathological abnormalities. A comprehensive set of retinal pictures tagged for lesions is provided by the MESSIDOR dataset, which helps.

In order to ensure that these images are suitable for further examination, pre-processing is an essential step. During the pre-processing pipeline, the images are resized to a standard resolution of 224 by 224 pixels. This helps to maximise computing efficiency while maintaining the important features. After that, normalisation is applied to make sure the scaled pixel values are within the range [0, 1]. Mitigating disparities in pixel intensities between images and standardising the data for later model training depend on this stage.

Sharpening, noise reduction, and contrast modification are potential extra pre-processing stages, given the sensitivity and specificity needed in medical imaging. In order to prevent bias in model training, the dataset is further divided into training, validation, and test sets while ensuring a balanced distribution of images. This comprehensive method of gathering data and pre-processing it sets up the foundation for reliable and accurate research in the subsequent stages of our study.

B. Vessel Segmentation

The segmentation of retinal arteries to extract pertinent information for cardiovascular risk assessment is a critical next step in our research. We use the UNET (U-shaped convolutional neural network) architecture, which is well-known for its efficiency in picture segmentation tasks, for this purpose. Mostly used for image processing at this point are the Python modules OpenCV and PyTorch, which include deep learning features.

An encoder and a decoder are aspects of the UNET architecture that enable the extraction of complex patterns and fine-grained segmentation. In order to make predictions on unobserved data later on, the model has to initially learn to distinguish between pixels that are vessels and those that are not during the training phase. To improve model generalisations, augmentation

approaches such as rotation, flipping, and zooming are used on the training dataset.

Neural network layers and optimisation algorithms are implemented with ease thanks to the use of Python's PyTorch tools. In pre-processing stages, the OpenCV library is essential for facilitating effective data manipulation and guaranteeing model compatibility with picture data. To improve segmentation accuracy, hyperparameters like learning rates and dropout rates are fine-tuned iteratively. After this phase is over, our model can recognise and divide retinal arteries with accuracy, which sets the way for additional research into the arteriolar and venular diameter ratio computations and cardiovascular risk assessments.

C. Arteriolar to Venular Diameter Ratio (AVR)

By dividing the average diameters of retinal arterioles by venules, the Arteriolar to Venular Diameter Ratio (AVR) ratio was calculated. The AVR was linked to a number of cardiovascular disorders and functioned as a marker of arteriolar constriction.

To calculate AVR, the following formula was applied:

$$AVR = CRAE / CRVE$$

Where CRAE stands for (Central Retinal Artery Equivalent): Average diameter of major retinal arteries and CRVE (Central Retinal Vein Equivalent): Average diameter of major retinal veins.

The segmented retinal pictures acquired in the previous phase were employed to extract vessel sizes in order to implement the AVR computation. Image processing operations and numerical computations were made easier with the help of Python modules like NumPy and OpenCV. For example, the diameter values were stored and managed using NumPy arrays.

The information required to measure CRAE and CRVE was provided by the segmented vessel pictures. For tasks like contour detection and diameter measurement, OpenCV functionalities were used. The method estimated the arteriole and venule diameters, iterated through the segmented arteries, and then computed the AVR. By include AVR, the study gained a quantitative component that improved the accuracy and dependability of the system's overall CVD risk prediction.

D. ResNet-50 and VGG-16 Model Training (Ensemble Learning for More Accuracy):

Training deep learning models—ResNet-50 and VGG-16, in particular—to create a reliable predictive framework for cardiovascular risks was the last phase of our study. Using ensemble learning with these two architectures made sense since it would take use of their complementary features, improving the prediction model's overall accuracy and generalisation. In computer vision tasks, such as picture classification, the ResNet-50 (Residual Network) and VGG-16 (Visual Geometry Group) architectures are well-established.

Large datasets were used to pre-train both models, which made it easier to extract high-level features important for retinal comprehension of images. Especially when working with relatively modest medical datasets, this pre-training is essential.

The goal of the ensemble method of learning was to leverage the variety of representations that ResNet-50 and VGG-16 had learnt. We aimed to reduce the biases in each model individually and increase the overall robustness of the cardiovascular risk prediction system by aggregating their outputs. Using our dataset of retinal images, we fine-tuned the pre-trained models to make sure they could accurately capture the distinctive characteristics indicative of cardiovascular risks. To improve model broadening, learning rates were changed, hyperparameters were optimised, and data augmentation approaches were adopted during the training-phase.

The combination of the ResNet-50 and VGG-16 models produced a more dependable and accurate prediction of cardiovascular risks. This strategy was motivated by the notion that integrating the advantages of several models can offset the shortcomings of each one, producing a predictive tool that is ultimately more potent and applicable to clinical settings. The efficacy of the ensemble model in practical applications was confirmed by a thorough evaluation of its performance using industry-standard criteria.

V. RESULTS AND DISCUSSION

The project conducted a thorough evaluation of various CNN models on the three retinal datasets which are CHASE, DRIVE and MESSIDOR respectively. The overall accuracy of VGG-16 Model has an edge over Resnet-50 by over 2%. While VGG-16 managed to get an overall accuracy of 97%, Resnet 50 manages to get an overall of 95.32% which makes us dependable on the former due to medical sensitivity.

Table I demonstrates the comparison of the models regarding their accuracy, precision and recall which was obtained from the retinal images.

Table	Performance Metrics			Algorithm	
Head	Precision	Recall	F1 score	Accuracy	
Class 1	0.98	0.96	0.97	97.46	VGG-16
Class 2	0.95	1	0.97		
Class 3	1	0.96	0.98		
Class 1	0.95	0.93	0.95	95.32	Resnet-50
Class 2	0.97	0.92	0.92		
Class 3	0.96	0.91	0.92		

The completion of the project produced promising findings that points out how well the proposed strategy for assessing cardiovascular risk using retinal pictures works. The UNET architecture proved its mettle in feature extraction by successfully segmenting retinal vessels, which laid the groundwork for future research.

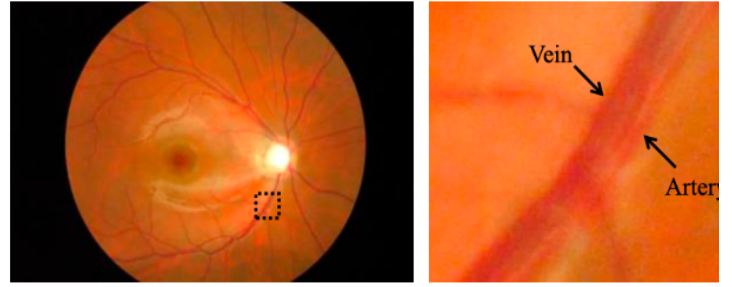


Fig. 1 Retinal images segmentation.

The above figure shows both, their segmentation of vein and artery.

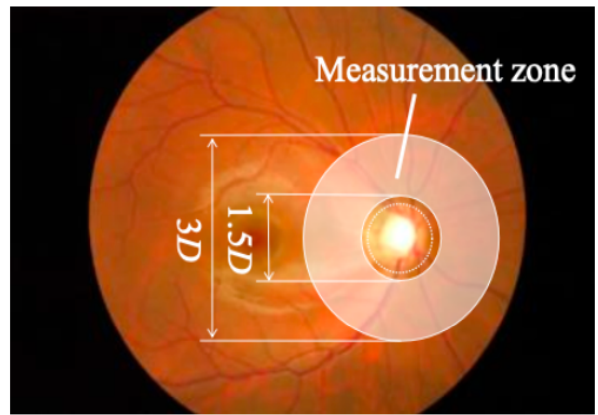


Fig. 2 AVR measuring zone D and optic disc diameter determination.

The above figure shows the exact location of the presence of optical disc which helps to calculate AVR to assess Cardiovascular risk.

The calculated Arteriolar to Venular Diameter Ratio (AVR) was a useful predictor; a low AVR was consistently associated with a higher risk of cardiovascular disease. ResNet-50 and VGG-16 ensemble learning for model training performed remarkably well in detecting nuances and intricate patterns in the retinal data. The system demonstrated a high degree of expected accuracy through the combination of multiple features that were achieved utilising the UNET architecture and AVR processing. These results confirm the value of retinal pictures processed with advanced deep learning techniques as a priceless tool for cardiovascular risk assessment. This will contribute to the corpus of information regarding predictive healthcare models and medical image analysis.

VI. CONCLUSION

In a nutshell this study project's successful completion marks a significant advancement in the field of using retinal pictures to estimate cardiovascular risk. A strong predictive modelling methodology has been shown through the combination of advanced techniques, such as ensemble learning with ResNet-50 and VGG-16, AVR computation, and UNET-based vessel segmentation. The potential clinical value of retinal image analysis is shown by the discovery that poor AVR is a powerful indication of elevated cardiovascular risk. Moreover, the ensemble learning methodology enhances the model's classification abilities, providing a sophisticated comprehension of complex patterns. This work adds to the field of medical

image analysis as well as the larger field of predictive healthcare modelling.

The results validate the feasibility of using retinal pictures as an effective diagnostic tool, setting the stage for future developments in cardiovascular risk assessment and predictive medicine.

REFERENCES

- [1] Wang, J., Leng, F., Li, Z. *et al.* Retinal vascular abnormalities and their associations with cardiovascular and cerebrovascular diseases: a Study in rural southwestern Harbin, China. *BMC Ophthalmol* **20**, 136 (2020). <https://doi.org/10.1186/s12886-020-01407-y>.
- [2] Tseng, R.M.W.W., Rim, T.H., Shantsila, E. *et al.* Validation of a deep-learning-based retinal biomarker (Reti-CVD) in the prediction of cardiovascular disease: data from UK Biobank. *BMC Med* **21**, 28 (2023). <https://doi.org/10.1186/s12916-022-02684-8>
- [3] Seecheran, N.A., Rafeeq, S., Maharaj, N. *et al.* Correlation of RETINAL Artery Diameter with Coronary Artery Disease: The RETINA CAD Pilot Study—Are the Eyes the Windows to the Heart?. *Cardiol Ther* **12**, 499–509 (2023). <https://doi.org/10.1007/s40119-023-00320-x>
- [4] Barriada, R.G.; Masip, D. An Overview of Deep-Learning-Based Methods for Cardiovascular Risk Assessment with Retinal Images. *Diagnostics* **2023**, *13*, 68. <https://doi.org/10.3390/diagnostics13010068>
- [5] Joseph Keunhong Yi, Tyler Hyungtaek Rim, Sungha Park, Sung Soo Kim, Hyeon Chang Kim, Chan Joo Lee, Hyeonmin Kim, Geunyoung Lee, James Soo Ghim Lim, Yong Yu Tan, Marco Yu, Yih-Chung Tham, Ameet Bakhai, Eduard Shantsila, Paul Leeson, Gregory Y H Lip, Calvin W L Chin, Ching-Yu Cheng, Cardiovascular disease risk assessment using a deep-learning-based retinal biomarker: a comparison with existing risk scores, *European Heart Journal - Digital Health*, Volume 4, Issue 3, May 2023, Pages 236–244, <https://doi.org/10.1093/ehjdh/zad023>
- [6] Nicholas Witt, Tien Y. Wong, Alun D. Hughes, Nish Chaturvedi. *et al* Abnormalities of Retinal Microvascular Structure and Risk of Mortality From Ischemic Heart Disease and Stroke Hypertension. 2006; 47:975–981 <https://doi.org/10.1161/01.HYP.0000216717.72048.6c>
- [7] Germanèse, C.; Meriaudeau, F.; Eid, P.; Tadayoni, R.; Gin hac, D.; Anwer, A.; Laure-Anne, S.; Guenancia, C.; Creuzot-Garcher, C.; Gabrielle, P.-H.; *et al.* A Retinal Oct-Angiography and Cardiovascular STatus (RASTA) Dataset of Swept-Source Microvascular Imaging for Cardiovascular Risk Assessment. *Data* **2023**, *8*, 147. <https://doi.org/10.3390/data8100147>
- [8] F. H. Malik, F. Batool, A. Rubab, N. A. Chaudhary, K. B. Khan and M. A. Qureshi, "Retinal disorder as a biomarker for detection of human diseases," 2020 IEEE 23rd International Multitopic Conference (INMIC), Bahawalpur, Pakistan, 2020, pp. 1-6, doi: 10.1109/INMIC50486.2020.9318059.
- [9] Colcombe, J.; Munda, R.; Kaiser, A.; Bijon, J.; Modi, Y. Retinal Findings and Cardiovascular Risk: Prognostic Conditions, Novel Biomarkers, and Emerging Image Analysis Techniques. *J. Pers. Med.* **2023**, *13*, 1564. <https://doi.org/10.3390/jpm13111564>
- [10] Hatanaka Y, Tachiki H, Ogohara K, Muramatsu C, Okumura S, Fujita H. Artery and vein diameter ratio measurement based on improvement of arteries and veins segmentation on retinal images. *Annu Int Conf IEEE Eng Med Biol Soc.* 2016 Aug;2016:1336-1339. doi: 10.1109/EMBC.2016.7590954. PMID: 28268572.
- [11] M Kanae Fukutsu, Michiyuki Saito, Kousuke Noda A Deep Learning Architecture for Vascular Area Measurement in Fundus Images *Ophthalmology Science*, Elsevier March 2021. DOI: <https://doi.org/10.1016/j.xops.2021.100004>
- [12] Arnould, L., Meriaudeau, F., Guenancia, C. *et al.* Using Artificial Intelligence to Analyse the Retinal Vascular Network: The Future of Cardiovascular Risk Assessment Based on Oculomics? A Narrative Review. *Ophthalmol Ther* **12**, 657–674 (2023). <https://doi.org/10.1007/s40123-022-00641-5>
- [13] Cynthia Ciwei Lim, Crystal Chong, Gavin Tan, Chieh Suai Tan, Carol Y Cheung, Tien Y Wong, Ching Yu Cheng, Charumathi Sabanayagam, A deep learning system for retinal vessel calibre improves cardiovascular risk prediction in Asians with chronic kidney disease, *Clinical Kidney Journal*, Volume 16, Issue 12, December 2023, Pages 2693–2702, <https://doi.org/10.1093/ckj/sfad227>
- [14] Karaali, Ali, Rozenn Dahyot and Donal J. Sexton. "DR-VNet: Retinal Vessel Segmentation via Dense Residual UNet." *International Conferences on Pattern Recognition and Artificial Intelligence* (2021).
- [15] Poplin, R., Varadarajan, A.V., Blumer, K. *et al.* Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning. *Nat Biomed Eng* **2**, 158–164 (2018). <https://doi.org/10.1038/s41551-018-0195-0>

D. CERTIFICATE



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(An autonomous institution affiliated to Anna University, Chennai)
Department of Electronics and Communication Engineering



Certificate of Appreciation

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YASHWIN P PRAKASH

for presenting the paper titled

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