

Web-Based Automated Geometric Vascular Feature Extraction from
Static Fundus Images for Hypertension Detection and CVD Risk
Stratification

An Undergraduate Thesis
Presented to the Faculty of the
College of Information and Communications Technology
West Visayas State University
La Paz, Iloilo City

In Partial Fulfillment
of the Requirements for the Degree
Computer Science

by
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June 2027

Approval Sheet

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Abstract

Hypertension and cardiovascular disease (CVD) remain leading causes of mortality in the Philippines, with over half of hypertensive cases undiagnosed or uncontrolled. This study presents a web-based automated system for geometric vascular feature extraction from static retinal fundus images to support hypertension detection and CVD risk stratification. The retina provides a non-invasive window into systemic microcirculation, where geometric alterations in vascular structures reflect underlying cardiovascular pathology. The proposed system processes static fundus images through a comprehensive pipeline comprising image validation, preprocessing, and deep learning-based vessel segmentation. Three primary geometric biomarkers are extracted: Arteriolar-

to-Venular Ratio (AVR) for quantifying arteriolar narrowing, vessel tortuosity for measuring vascular curvature, and vascular fractal dimension for assessing branching complexity. Secondary supporting features including color statistics, Gray-Level Co-occurrence Matrix (GLCM) texture analysis, vessel topology metrics, and segmentation quality indicators—enhance prediction reliability. These multidimensional features are integrated into a machine learning classifier that generates hypertension probability scores and categorical classifications, subsequently stratifying patients into Low, Intermediate, or High CVD risk categories. Delivered through a cloud-based web platform, the system enables remote access and scalable deployment across healthcare institutions, from tertiary hospitals to rural health units. By automating interpretable retinal vascular analysis, this research addresses critical gaps in accessible cardiovascular screening, supporting early detection and preventive care in resource-constrained settings.

Keywords: cardiovascular disease, fundus image analysis, geometric feature extraction, hypertension detection, machine learning, retinal biomarkers, risk stratification, web-based system.

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CHAPTER 1 INTRODUCTION TO THE STUDY

Background of the Study and Conceptual Framework

Cardiovascular diseases (CVDs) and hypertension represent one of the most significant public health challenges of the 21st century, imposing an enormous burden on healthcare systems worldwide. According to the World Health Organization (WHO), approximately 1.4 billion people lived with hypertension in 2024, yet just over one in five have it under control either through medication or addressing modifiable health risks [1]. The Global Burden of Disease Study 2023 reported that CVDs were the leading cause of disability-adjusted life years (DALYs) and deaths globally, with 437 million CVD DALYs and 19.2 million CVD deaths (1 in 3 globally) recorded in 2023 [2]. Ischemic heart disease, intracerebral hemorrhage, ischemic stroke, and hypertensive heart diseases were identified as the leading cardiovascular cause of DALYs. Alarming, 79.6% of the CVD burden is attributable to modifiable risk factors, with high systolic blood pressure being the primary driver responsible for 347 million DALYs in 2023 [2].

The Philippines faces a particularly concerning situation regarding hypertension and cardiovascular disease

burden. In 2024, the WHO reported that 16.8 million Filipino adults aged 30 to 79 have hypertension, with 54% (9.1 million) remaining undiagnosed or uncontrolled [3].

According to the Philippine Statistics Authority, ischemic heart diseases led all causes of death in the country from January to October 2024, accounting for 85,868 deaths or 19.4% of total mortality [4]. The ASEAN burden of disease study revealed that the Philippines has one of the highest age-standardized cardiovascular disease mortality rates in the region, exceeding the middle-Socio-demographic Index (SDI) average by 1.2 times [5]. Furthermore, a prospective cohort study conducted in Malaysia and Philippines found that the incidence of CVD was higher in the Philippines (11.0 per 1,000 person-years) compared to Malaysia (8.3 per 1,000 per person-years), with CVD contributing to a higher proportion of deaths in the Philippines (58% versus 36%) [6].

The importance of early detection and risk stratification in reducing complications associated with hypertension and CVD cannot be overstated. The American Heart Association emphasizes that addressing lifestyle factors and implementing early treatment protocols may prevent, delay, or treat elevated blood pressure thereby reducing overall CVD risk [7]. Uncontrolled hypertension

serves as a precursor to numerous serious complications including heart attack, stroke, chronic kidney disease, and dementia [1]. The WHO estimates that uncontrolled high blood pressure claims more than 10 million lives every year, despite being both preventable and treatable [1]. Early intervention strategies, including regular blood pressure monitoring, adherence to healthy lifestyle advice, and patient-centered treatment plans, have demonstrated significant potential in mitigating disease progression and improving long-term outcomes [7].

Retinal fundus imaging has emerged as a promising non-invasive diagnostic tool for assessing systemic cardiovascular health. The retina provides a unique window into the body's microcirculation, as retinal blood vessels share anatomical and physiological characteristics with cerebral and coronary vasculature [8]. Advanced imaging techniques such as fundus photography enable high-resolution capture of retinal vascular structures, allowing for detailed analysis of vessel morphology, caliber, and patterns. Research has established substantial correlations between CVD risk and various retinal parameters, demonstrating that alterations in retinal vascular geometry reflect systemic cardiovascular conditions [8]. The concept

of “oculomics” refers to the study of ocular biomarkers that reflect systemic disease, offering a non-invasive, rapid, and promising approach to clinical screening [9].

This study focuses on three key geometric vascular biomarkers extracted from retinal fundus images: Arteriolar Narrowing (decreased Arteriolar-to-Venular Ratio), Vessel Tortuosity, and Vascular Fractal Dimension. Each of these biomarkers provides distinct insights into cardiovascular health status.

The Arteriolar-to-Venar Ratio (AVR) represents the ratio of the central retinal arteriolar equivalent (CRAE) to the central retinal venular equivalent (CRVE), serving as a quantitative measure of generalized arteriolar narrowing [10]. Retinal vascular caliber, measuring 150-300 micrometers, provides a novel model for studying correlates and consequences of generalized microvascular dysfunction [10]. Several prospective, population-based cohort studies have established that retinal vascular caliber changes, particularly narrower retinal arterioles, predict incident hypertension [10]. A lower AVR (narrower arterioles relative to venules) is consistently linked to hypertension and is considered a potential indicator of cardiovascular risk [8].

Clinical observations in patients with cardiovascular disease commonly include retinal arteriolar narrowing, decreased arteriovenous ratio, and reduced arteriole width [8].

Vessel tortuosity refers to the degree of curvature or winding in retinal blood vessels, representing another important morphological characteristic of the retinal vascular network. Recent genome-wide association studies of retinal vessel tortuosity have identified 175 significantly associated genetic loci, with higher retinal tortuosity significantly associated with higher incidence of angina, myocardial infarction, stroke, deep vein thrombosis, and hypertension [11]. The study demonstrated that retinal tortuosity loci serve pleiotropic functions as cardiometabolic disease variants and risk factors, with Mendelian randomization revealing causal effects between tortuosity, body mass index, and low-density lipoprotein [11]. Research in children has shown that retinal arteriolar tortuosity is positively associated with levels of triglyceride, total and LDL cholesterol, systolic and diastolic blood pressure [12].

Vascular fractal dimension (FD) is a measure used to quantify the complex or self-similarity of the retinal vasculature branching pattern [8]. The fractal dimension is computed by covering the image with a sequence of grids of descending sizes, recording the number of square boxes intersected by the image, and determining the regression slope from the log-log plot [8]. FD has been considered as a potential biomarker for the detection of several diseases including diabetes and hypertension. However, research has demonstrated that the reliability of FD measurement varies considerably according to image quality, modality, and the technique used for measuring it [13]. Despite these challenges, when properly measured, the vascular fractal dimension provides valuable information about the geometric complexity of retinal microvasculature.

The association between retinal vascular biomarkers and cardiovascular risk has been extensively studied in epidemiological studies. The Atherosclerosis Risk in Communities (ARIC) study, Rotterdam Study, and Blue Mountain Eye Study provided robust evidence that retinal features correlated with cardiovascular, renal, and neurological outcomes [9]. Decreased central arteriolar equivalent and increased central retinal venular equivalent have been

associated with echocardiographic measures of both left ventricular systolic and diastolic dysfunction [8]. Poplin et al. demonstrated that deep learning models could predict cardiovascular risk factors from retinal fundus photographs with remarkable accuracy, including age (within 3.36 years), gender (0.97 AUC), smoking status (0.71 AUC), HbA1c (within 1.39%), and systolic blood pressure (within 11.23 mmHg) [14].

Deep learning-based approaches have further validated the predictive capability of retinal biomarkers. The Reti-CVD score, a deep learning-based retinal biomarker, identified Pool Cohort Equation-based intermediate and high-risk CVD with a sensitivity of 82.7%, QRISK3-based intermediate and high-risk patients with a sensitivity of 82.6%, and modified Framingham Risk Score-based intermediate and high-risk CVD with a sensitivity of 82.1% [9]. Another study achieved an area under the receiving operating characteristic curve (AUROC) of 0.971 for borderline-risk CVD and 0.976 for intermediate high-risk CVD using AI models analyzing retinal images [9]. These findings underscore the substantial potential of retinal vascular biomarkers as non-invasive indicators of cardiovascular health status.

Despite the established clinical value of retinal examination, traditional manual assessment methods face significant limitations, particularly in resource-constrained settings such as the Philippines. Traditional diagnosis of retinal diseases relies on manual interpretation of color eye fundus photographs by expert ophthalmologists, a process that is both time-consuming and costly [15]. Studies have reported that a single image can take up to 69 plus or minus 24 seconds to grade manually, and the inherent subjectivity in human assessment often leads to inter-observer variability [15]. Such limitations hinder large-scale screening efforts, especially in regions with a shortage of specialists.

The development of a web-based automated system for geometric vascular feature extraction addresses the critical need for accessible, scalable, and consistent cardiovascular risk screening, particularly in rural and resourced-constrained Philippine healthcare settings. Automated systems leveraging deep learning and computer vision techniques have demonstrated the capability to process thousands of images in a fraction of the time required by manual methods, significantly enhancing screening efficiency

and potentially reducing the rate of undiagnosed conditions [15]. A hybrid multi-stage approach combining computer vision and deep learning techniques achieved an overall accuracy of 85% in clinical validation for CVD risk assessment from retinal fundus images [8].

The web-based architecture offers several distinct advantages for healthcare delivery in the Philippine context. Cloud-based AI systems allow remote image interpretation, democratizing access to advanced diagnostics and helping reduce disparities in healthcare delivery [16]. Real-world feasibility studies have demonstrated that automated retinal photography and AI-based cardiovascular disease risk assessment are acceptable and feasible in primary care settings [16]. The non-invasive nature of fundus imaging, combined with automated analysis, makes this approach particularly appealing for large-scale healthcare initiatives aimed at preventing and managing cardiovascular diseases [8].

The potential impact of such a system extends beyond individual patient care to population-level health outcomes. By identifying vascular abnormalities before the onset of overt cardiovascular events, the approach aligns with the

principles of preventive medicine and offers a proactive strategy for cardiovascular health management [8]. The integration of this technology into routine clinical practice could improve patient outcomes by enabling earlier detection, facilitating timely interventions, and supporting the goals of Universal Health Coverage in the Philippines. As healthcare systems worldwide face rising demands from chronic diseases, automated retinal image analysis offers a cost-effective and scalable approach to early detection and risk prediction.

The foundation of this study is rooted in microvascular theory in pathophysiology. This theoretical framework provides the scientific basis for understanding how retinal vascular changes reflect the systemic cardiovascular conditions and how these changes can be used as biomarkers for detecting diseases. The microvascular theory posits that the retinal vasculature serves as a direct window into the systemic microcirculation, sharing anatomical, physiological, and pathological characteristics with cerebral and coronary vessels [8]. This theoretical foundation, supported by extensive epidemiological evidence from the ARIC study, Rotterdam study, and Blue Mountains Eye Study, establishes that changes in retinal vascular geometry

reflect underlying microvascular dysfunction throughout the body [9]. The theory of endothelial dysfunction provides further mechanistic understanding, suggesting that hypertension-induced damage to the vascular endothelium manifests as measurable changes in vessel caliber, tortuosity, and branching patterns [10]. Fractal geometry theory, pioneered by Mandelbrot, provides the mathematical foundation for understanding the self-similar branching pattern of biological vascular networks [13]. The application of fractal analysis to retinal vasculature is based on the principle that healthy vascular systems exhibit optimal geometric complexity for efficient nutrient delivery, and deviations from this optimal fractal dimension may indicate pathological states. This theoretical perspective supports the use of vascular fractal dimension as a quantitative biomarker for cardiovascular risk assessment.

In addition, the theoretical framework of health informatics guides the design and implementation of the web-based platform as a clinical decision support system. The theory of clinical decision support system (CDSS) emphasizes the importance of providing timely, relevant information to healthcare providers at the point of care to enhance

decision-making quality [17]. This study applies the principle of the Five Rights of CDSS: delivering the right information, to the right person, in the right format, through the right channel, at the right time.

The theoretical framework is operationalized through the following conceptual framework:

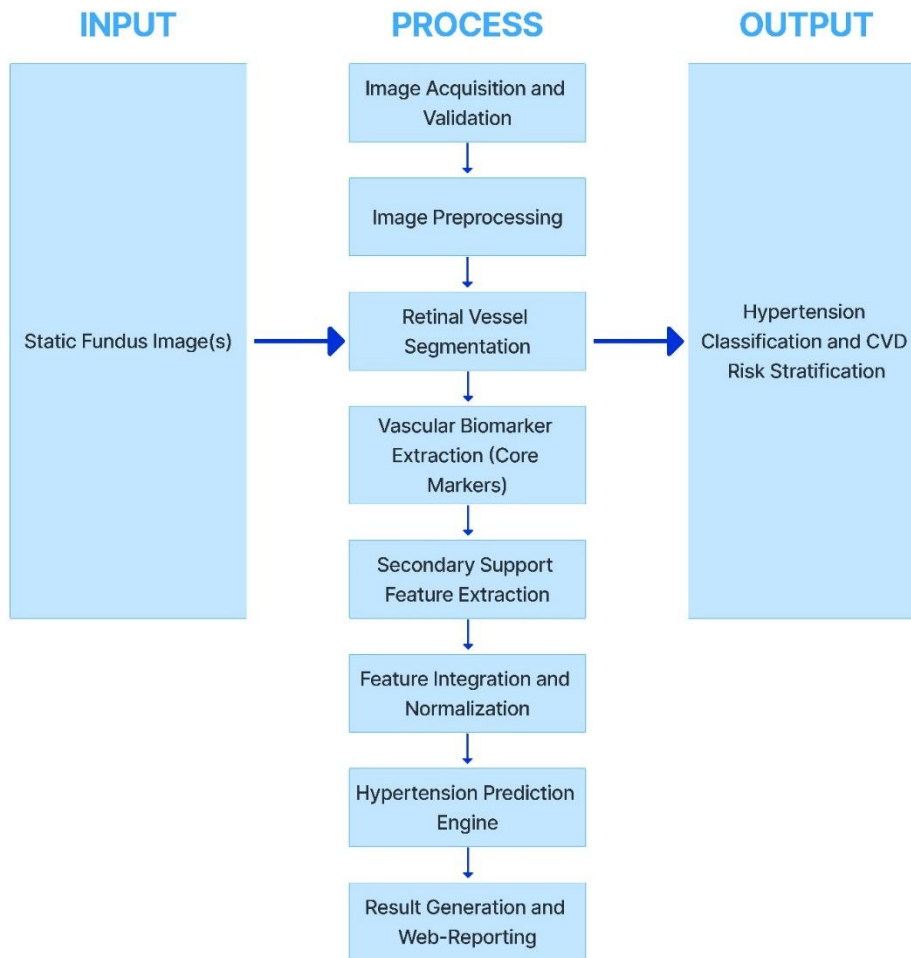


Figure 1. Conceptual Framework

Figure 1 illustrates the conceptual framework of this study, following the IPO (Input-Process-Output) Model. This shows the interaction of the core components of the system. The system accepts static retinal fundus images as its primary input. This input is then processed through multiple layers from preprocessing all the way to the geometric feature extraction as well as the secondary support feature extraction. At last, the output layer will present hypertension detection results and CVD risk stratification classification.

Objectives of the Study

Generally, this study aims to develop and technically validate a web-based computer vision system that automatically extracts geometric retinal vascular features from static fundus images to support hypertension detection and cardiovascular disease risk stratification.

Specifically, it aims to:

1. To develop an automated image preprocessing and vessel segmentation pipeline for static retinal fundus images, incorporating noise reduction, contrast enhancement, and deep learning-based vessel detection techniques, with effectiveness evaluated through established

- performance metrics including accuracy, precision, and recall, and F1-Score;
2. To implement distance-transform-based vessel caliber estimation with artery/vein separation algorithm for arteriolar narrowing (AVR), arc-chord ratio algorithm for vessel tortuosity, and box-counting algorithm for vascular fractal dimension, from segmented retinal vessel networks;
 3. To design and implement a web-based platform for automated retinal image analysis and visualization, enabling remote access and scalable deployment for healthcare institutions;
 4. To evaluate the system's effectiveness in supporting hypertension detection and CVD risk stratification using extracted retinal vascular features, using ISO/IEC 25010:2023 systems and software quality requirements and evaluation.

Significance of the Study

The study would be beneficial to the following groups:

Patients and High-Risk Individuals

Through this study, it enables non-invasive detection of hypertension and cardiovascular risk that are often overlooked by standard risk prediction charts. Enhances accessibility for individuals in rural regions where specialized care is either limited or unavailable. And to also provide a critical early warning system for patients who may be misclassified as "low risk" but are suffering from acute endothelial dysfunction.

Healthcare Professionals

For healthcare professionals, particularly those in primary care and rural settings, the proposed system offers a valuable decision-support tool that augments clinical assessment capabilities. The automated extraction of retinal vascular biomarkers provides quantitative, objective measurements that complement traditional diagnostic methods. Physicians can utilize the system's risk stratification output to identify patients requiring further cardiovascular evaluation, potentially reducing missed diagnoses and enabling earlier intervention. The web-based architecture ensures that specialists in urban centers can support colleagues in remote areas through the platform's remote interpretation capabilities.

Patients and the General Public

Patients and the general public stand to benefit from improved access to cardiovascular screening, particularly in underserved communities. The non-invasive nature of fundus imaging eliminates the discomfort and risks associated with invasive diagnostic procedures. Early detection of cardiovascular risk enables timely lifestyle modifications and medical interventions, potentially preventing the progression to severe complications such as myocardial infarction, stroke, and chronic kidney disease.

Hospitals and Screening Institutions in the Philippines

Hospitals and screening institutions in the Philippines face significant challenges related to specialist shortages and resource constraints. The proposed system addresses these limitations by automating the analysis of retinal images, reducing dependence on scarce ophthalmology specialists for initial screening. Rural health units and community clinics can integrate the system into their existing workflows, enabling local cardiovascular risk assessment without requiring patient referrals to distant facilities. The scalability of the web-based platform allows institutions to expand screening capacity without proportional increases in personnel costs, supporting the goals of Universal Health Coverage in the Philippines.

Future Researchers and Policymakers

Future researchers can build upon the framework and implementation presented in this study to create enhanced versions or specialized applications. The modular architecture facilitates the incorporation of additional biomarkers, integration with electronic health records, and adaptation for other disease screening applications. Policymakers can utilize the evidence generated by this study to inform decisions regarding the adoption of AI-based diagnostic tools in national healthcare programs. The system's potential to improve screening efficiency and reduce healthcare costs aligns with policy objectives for sustainable healthcare financing and equitable service delivery.

Delimitation of the Study

The study focuses exclusively on static retinal fundus images and does not include analysis of video-based or dynamic imaging modalities. Static fundus photography represents the most widely available and cost-effective retinal imaging modality in clinical practice. The system is designed to process single-field fundus photographs using

standard fundus cameras, with image formats limited to commonly used standards such as JPEG, PNG, and TIFF.

The geometric vascular biomarkers addressed in this study are limited to arteriolar narrowing (AVR), vessel tortuosity, and vascular fractal dimension. While other retinal features such as microaneurysms, hemorrhages, cotton wool spots, and copper branching may provide additional diagnostic information, the study concentrates on these three biomarkers due to their established association with hypertension and cardiovascular diseases [8], [10], [11], [13].

In addition to the core biomarkers, the system extracts secondary support features including Color Statistics, Texture Features (GLCM), Vessel Topology descriptors, and Quality/Reliability Indicators. These support features provide additional contextual information that enhances the robustness and reliability of the screening system, particularly when processing images of varying quality. However, these secondary features are not standalone diagnostic indicators and serve to complement the primary vascular biomarkers.

The system is designed as a screening and decision-support tool, not as a substitute for clinical diagnosis. The risk stratification output is intended to assist healthcare professionals in identifying patients who may benefit from further evaluation, rather than providing definitive diagnostic conclusions. Final clinical decisions remain the responsibility of qualified healthcare providers.

The study's training and validation is conducted using publicly available retinal image datasets and datasets from partner hospitals and clinics. And may be limited by the characteristics of these datasets, including patient demographics and disease prevalence. The system's performance may vary when applied to populations with different characteristics.

Definition of Terms

For better understanding, the following terms were defined conceptually and operationally:

Arteriolar-to-Venular Ratio.

The Arteriolar-to-Venular Ratio is a quantitative measure representing the ratio of the central retinal arteriolar equivalent (CRAE) to the central retinal venular equivalent

(CRVE), used to assess generalized arteriolar narrowing in the retinal vasculature [10].

In this study, AVR refers to the computer ratio of CRAE and CRVE derived from automated analysis of segmented retinal vessels, serving as a biomarker for hypertension detection and CVD risk assessment.

Cardiovascular Disease (CVD) .

Cardiovascular disease encompasses a group of disorders affecting the heart and blood vessels, including coronary heart disease, cerebrovascular disease, peripheral arterial disease, rheumatic heart disease, congenital heart disease, and deep vein thrombosis [1].

In this study, CVD refers to the spectrum of cardiovascular conditions that the system aims to stratify for risk assessment, with particular focus on hypertension-related cardiovascular complications.

Fundus Image .

A fundus image is a photographic capture of the interior surface of the eye, including the retina, optic disc, macula, and posterior pole, obtained using a fundus camera [18].

In this study, fundus images refer to the static digital photographs of the retina used as input for the automated geometric vascular feature extraction system.

Gray-Level Co-occurrence Matrix (GLCM).

The Gray-Level Co-occurrence Matrix is a statistical method for examining texture that considers the spatial relationship of pixels in an image, calculating how often pairs of pixel values with specific intensities occur in specified spatial relationships [19].

In this study, GLCM refers to the texture analysis technique used to extract second-order statistical features from retinal images, quantifying surface smoothness, pixel similarity patterns, and local structural organization.

Hypertension.

Hypertension, or high blood pressure, is a medical condition characterized by persistently elevated blood pressure in the arteries defined by WHO as systolic blood pressure of 140 mmHg or higher and/or diastolic blood pressure of 90mmHg or higher [1], [3].

In this study, hypertension refers to the cardiovascular condition that the system aims to detect through analysis of retinal vascular biomarkers, with risk

stratification based on extracted geometric features and patient data.

Image Texture.

Image texture is typically defined as the spatial distribution or arrangement of pixel intensities (or colors) within a region, often described as local variations in brightness that convey properties like smoothness, roughness, or regularity [19].

In this study, image texture refers to the surface characteristics of retinal regions captured through GLCM analysis, providing fine-grained visual information beyond vessel geometry.

Oculomics.

Oculomics refer to the study of ocular biomarkers that reflect systemic disease, utilizing advanced imaging and computational techniques to extract quantitative features from the eye for disease screening and risk assessment [9].

In this study, oculomics refers to the analytical approach of using retinal fundus images and their geometric vascular features as indicators of systemic cardiovascular health.

Segmentation Quality Indicators.

Segmentation quality indicators are quantitative metrics that measure how reliably a segmentation reproduces the reference vessel anatomy in terms of detection completeness, false detections, and vascular topology [20].

In this study, segmentation quality indicators refer to the computed metrics estimating vessel segmentation reliability, including vessel density, network completeness, and realistic branching patterns, used to prevent incorrect interpretation when segmentation quality is poor.

Risk Stratification.

Risk stratification is the process of categorizing individuals into different risk groups based on the probability of developing a disease or experiencing an adverse health outcome, enabling targeted interventions [9].

In this study, risk stratification refers to the classification of patients into Low, Intermediate, or High CVD risk categories based on the analysis of extracted retinal biomarkers and patient profile.

Vascular Fractal Dimension.

Vascular fractal dimension is a quantitative measurement of the geometric complexity and self-similarity of the retinal vasculature branching pattern, typically computed using box-counting method [13].

In this study, vascular fractal dimension refers to the computed measure of retinal vessel branching complexity extracted from segmented fundus images, used as biomarker for hypertension and cardiovascular risk assessment.

Vessel Segmentation.

Vessel segmentation is the process of extracting and delineating blood vessel structures from medical images, producing binary masks that distinguish vessels from background tissue [21].

In this study, vessel tortuosity refers to the computed measure of retinal vessel curvature and winding pattern extracted from segmented fundus images, serving as a biomarker for hypertension and CVD risk.

Vessel Topology.

Vessel topology is the way the retinal vascular network is organized as a graph in which vessels are decomposed into segments and junctions, and these are represented as nodes

and edges in a vessel graph that captures how segments connect, bifurcate, and form paths through the network [22].

In this study, vessel topology refers to the descriptors capturing the structural layout of the retinal vessel network, including branch point density, vessel endings, and total network length, providing network-level context to the vascular biomarkers.

Web-Based System.

A web-based system is a software application that operates through web browser and internet protocols, enabling remote access and distributed usage without requiring local installation [23].

In this study, a web-based system refers to the cloud-deployed platform that provides automated retinal image analysis, visualization, and reporting capabilities accessible through standard web browsers.

CHAPTER 2 REVIEW OF RELATED STUDIES

Review of Existing and Related Studies

Current Systems

I. Deep Learning for Extracting Systemic Biomarkers from the Retina

The foundation of modern automated retinal risk stratification was significantly advanced by Google Research. Poplin et al. [14] developed deep learning models trained on over 284,000 patients from the UK Biobank and EyePACS datasets. Their system successfully demonstrated that AI could extract cardiovascular risk factors previously thought to be unquantifiable from static fundus images alone. The system accurately predicted patient age, gender, smoking status, systolic blood pressure (within an error margin of 11.23 mmHg), and the likelihood of major adverse cardiac events (MACE) [14]. This established the "current baseline" that standard color fundus photography contains enough latent microvascular data to predict systemic cardiovascular health without requiring invasive blood draws.

II. **Automated Geometric Vascular Feature Extraction (The QUARTZ System)**

Current automated systems have moved beyond "black box" deep learning by extracting specific, quantifiable geometric vascular features. A prominent current implementation is the QUARTZ system (Quantitative Analysis of Retinal vessels Topology and size). Validated using retinal images from over 88,000 UK Biobank participants, this system is a fully automated AI algorithm that measures the width, vessel area, and degree of curviness (tortuosity) of the arterioles and venules in the retina [24]. Research published in the British Journal of Ophthalmology demonstrated that QUARTZ's automated feature extraction, combined with basic patient history (age and smoking status), successfully captured between half and two-thirds of circulatory disease deaths in high-risk populations, proving that automated geometric extraction is highly effective for stroke and hypertension prediction [24].

III. **Clinical AI-SaMD for CVD Risk Stratification (Reti-CVD)**

In terms of commercially deployed and regulated Software as a Medical Device (SaMD), Reti-CVD (developed by MediWhale) represents the current state-of-the-art. Reti-CVD is a deep learning based cardiovascular disease risk triage tool that uses retinal photographs to estimate the probability of Coronary Artery Calcium (CAC) presence [25]. Studies across the UK Biobank, AREDS (Age-Related Eye Disease Studies), and the CMERC-HI cohort have proven that Reti-CVD identifies intermediate and high-risk CVD patients with over 80% sensitivity and specificity [26]. It performs comparably to traditional blood-test-reliant tools like the Pooled Cohort Equation (PCE), QRISK3, and the Framingham Risk Score [27]. It was recently authorized by Korean regulatory bodies and is actively being integrated into primary care settings as a non-invasive and one-stop CVD triage tool.

IV. **Web-Based, Cloud, and Point-of-Care Implementations**

The current trajectory of retinal screening systems is heavily focused on web-based accessibility and point-of-care deployment, replacing the need for specialist ophthalmologist referrals for primary screening. Systems like AEYE Health's AEYE-DS (an FDA-cleared, fully autonomous AI system) allow primary care physicians to upload static fundus images from portable cameras to a cloud server, receiving diagnostic reports for diabetic retinopathy in under a minute [28]. Furthermore, recent studies (2024) have successfully validated web-connected machine learning models for estimating blood pressure and glycated hemoglobin from fundus photos in resource-limited settings like Kenya [29]. These systems utilize a cloud-based architecture to bring advanced geometric and predictive analysis to rural clinics.

**V. The Burden of Hypertension and Current Screening Gaps
in the Philippines**

Bringing this technology to the local context is vital, as hypertension remains one of the most critical public health challenges in the Philippines. According to the Philippine Statistics Authority (PSA), cardiovascular diseases, largely driven by uncontrolled hypertension, consistently rank as the leading cause of mortality in the country [4]. Despite clear guidelines for detection and management, a significant portion of the Philippine population remains undiagnosed or poorly controlled. Current mass screening efforts in grassroots settings, such as Barangay Health Centers, rely almost entirely on traditional sphygmomanometry (blood pressure cuffs). While effective for acute readings, this method fails to capture the chronic, cumulative microvascular damage caused by long-term elevated blood pressure, which is a stronger predictor of future major adverse cardiac events (MACE).

VI. Hypertensive Retinopathy and Geometric Vascular Markers

The retina provides the only non-invasive window to directly observe the human microvasculature. Chronic systemic hypertension manifests in the eye as hypertensive retinopathy, characterized by specific geometric alterations in the blood vessels. Current medical literature establishes that prolonged high blood pressure leads to measurable geometric changes, including arteriolar narrowing (decreased Arteriole-to-Venule Ratio or AVR), increased vessel tortuosity (curviness), and altered fractal dimensions [10]. While ophthalmologists can manually observe these signs to stage hypertensive damage, this manual grading is highly subjective, time-consuming, and requires specialized medical training that is largely unavailable in primary care settings in the Philippines.

VII. Limitations of Existing Telemedicine for Hypertension in the PH

While teleophthalmology is slowly gaining traction in the Philippines, current implementations are misaligned with hypertension screening. Existing local tele-screening architectures are almost exclusively designed to forward images to remote human specialists for manual grading. Furthermore, the few commercial AI models currently being introduced into the Philippine market operate as proprietary, "black-box" systems that output a generalized risk score without explaining the physiological reasoning. There is currently a profound lack of accessible, open architectures that specifically target and measure the underlying *geometric* causes of hypertensive retinopathy to provide interpretable data for local health workers.

VIII. Synthesis and Relevance to the Proposed System

Table 1. Conceptual Mapping Table for Current Systems

System	Core Methodology	Key Features Extracted	Architecture & Deployment	Interpretability	Target Application & Context
Google AI (Poplin et al.) [14]	Deep Learning Neural Networks	Implicit (None explicitly measured)	Resource-heavy Cloud / Research	Low ("Black Box")	General CVD and systemic risk prediction from UK Biobank.
QUARTZ System [24]	Automated AI Feature Extraction	Primary Geometric (Vessel width, tortuosity, area)	High-compute Desktop / Server	High (Outputs specific measurements)	Stroke and circulatory mortality prediction in high-risk populations.
Reti-CVD [25]	Deep Learning (Clinical SaMD)	Implicit (Predicts CAC score)	Clinical primary care integrations	Low ("Black Box")	Commercial non-invasive CVD risk triage tool.

Web/Cloud ML (AEYE-DS [28], White et al. [29])	Autonomous Cloud AI	General lesions & implicit systemic markers	Web-based, Point-of-Care	Low to Moderate	Fast DR screening and BP estimation for resource-limited clinics.
Web-Based Automated Geometric Vascular Feature Extraction	Hybrid Feature Extraction	Primary Geometric (Tortuosity, AVR) + Secondary (GLCM Texture, Color, Topology, Quality)	Lightweight Web-Based Application	High (Clinically understandable visual markers)	Hypertension / CVD triage specifically tailored for local hospitals.

Comparing current AI advancements with local Philippine healthcare needs reveals a significant technological gap. While modern AI models like Reti-CVD and Poplin's deep learning architectures [14] are highly accurate, they function as "black boxes." Because they bypass the measurement of specific geometric features, it is difficult for doctors to understand the medical reasoning behind the AI's results. On the other hand, systems like QUARTZ [24] successfully extract these geometric features but require heavy computational resources. At the same time, traditional local screening methods—such as basic blood pressure cuffs—cannot assess actual blood vessel damage.

Furthermore, existing automated systems generally rely on either basic geometric shape alone or complex, unexplainable neural networks. They often exclude secondary supporting features, such as color statistics, image texture (GLCM), vascular topology, and image quality indicators. Without these features, current systems are less reliable, particularly when processing the varied-quality retinal images commonly found in rural telemedicine settings.

Therefore, there is a clear need for a web-based system that extracts interpretable primary geometric features (like vessel tortuosity and width) and strengthens them with secondary supporting features for better accuracy. The system addresses this gap by offering a computationally lightweight, clinically understandable, "hybrid" feature extraction tool. This ensures accessible and reliable hypertension and CVD risk screening for local primary care centers.

Related Systems or Solutions

In the development of automated diagnostic tools for cardiovascular health, various systems have been designed to leverage retinal fundus images for cardiovascular disease (CVD) risk stratification and hypertension detection. These systems utilize advancements in deep learning, computer vision, and health informatics to extract systemic biomarkers non-invasively, addressing the critical need for scalable diagnostic solutions.

One pioneering system was developed by Poplin *et al.* [14], which utilized deep learning models trained on over 284,000 patients from the UK Biobank and EyePACS datasets. This system successfully demonstrated that artificial

intelligence could extract cardiovascular risk factors previously thought to be unquantifiable from the eye. The model was able to accurately predict patient age, gender, smoking status, systolic blood pressure, and the likelihood of major adverse cardiac events (MACE) directly from static fundus images. However, while highly accurate, this architecture functions as a "black box." Because the system bypasses the measurement of specific geometric retinal features, it becomes difficult for healthcare providers to interpret the medical reasoning behind the AI's predictions and understand which physiological indicators influenced the output [14].

To address the need for clinical explainability, systems focusing on automated geometric vascular feature extraction have been introduced, such as the QUARTZ (Quantitative Analysis of Retinal Vessels Topology and Size) system [28]. QUARTZ was validated using retinal images from more than 88,000 participants from the UK Biobank dataset and was designed to automatically quantify vascular structures within retinal images. The system measures several geometric vascular characteristics, including vessel width, vessel area, and the degree of vessel curviness, also known as tortuosity, for both retinal arterioles and venules. By extracting these measurable vascular features,

the system provides interpretable indicators that can be associated with circulatory disease risks. However, despite its strong capability in measuring specific vascular biomarkers, QUARTZ requires significant computational resources and dedicated local software infrastructure to operate effectively. These requirements present challenges for deployment in lightweight systems or low-resource telemedicine environments where computational capacity may be limited [28].

In the realm of commercially deployed Clinical AI Software as a Medical Device (AI-SaMD), Reti-CVD developed by MediWhale represents a modern state-of-the-art tool [27]. This system utilizes deep learning algorithms to estimate the probability of Coronary Artery Calcium (CAC) presence using retinal fundus photographs. Studies evaluating the system report that it can identify intermediate- and high-risk cardiovascular disease patients with over 80% sensitivity and specificity. Its performance has been shown to be comparable to traditional cardiovascular risk assessment tools such as the Pooled Cohort Equation (PCE) and QRISK3, which typically rely on blood tests and demographic data. Despite its strong predictive capability and regulatory authorization, Reti-CVD remains a proprietary commercial system. As a result, it primarily outputs

generalized cardiovascular risk scores without providing detailed explanations regarding the underlying physiological reasoning or identifying specific regions of microvascular damage that influenced the prediction [27].

Recent advancements in retinal analysis have also explored the identification of new systemic biomarkers, particularly indicators related to vascular aging. One such approach was proposed through the development of a deep learning-based Reti-aging score model, which predicts vascular aging directly from retinal fundus images [30]. The model was validated against pulse wave velocity (PWV), which is considered a gold-standard measurement for arterial stiffness. Experimental results showed that the Reti-aging score achieved an Area Under the Curve (AUC) value of 0.826, demonstrating strong predictive performance. Furthermore, the model was able to successfully identify individuals at risk for developing new-onset hypertension (NH) and carotid artery plaque (NCP). Although this approach introduces an innovative biomarker related to vascular aging, the model still relies heavily on a direct image-to-prediction deep learning pipeline rather than extracting isolated geometric vascular measurements that clinicians can independently examine or validate [30].

Other research efforts have shifted their focus toward analyzing dynamic retinal features using video data instead of static images. The U3D-Net system, introduced by Panahi *et al.* [31], is a specialized end-to-end deep learning architecture designed to autonomously classify Spontaneous Retinal Venous Pulsations (SVPs) from retinal videos. The model incorporates an optic disc localization module followed by a three-dimensional convolutional neural network classifier that captures both spatial and temporal information within the video sequence. Experimental results showed that the system achieved an overall classification accuracy of 84% and a sensitivity of 90%. While this approach demonstrates strong capability in detecting temporal vascular behavior, its reliance on retinal video data presents practical limitations. Video-based retinal imaging is less commonly available in many healthcare settings, particularly in primary care environments where static fundus photography remains the most widely used and cost-effective screening modality [31].

Overall, existing research in automated retinal analysis demonstrates significant progress in utilizing retinal biomarkers for cardiovascular risk assessment. However, several limitations remain across current approaches. Advanced deep learning systems, such as those

proposed in [14] and [27], achieve strong predictive performance but lack clinical explainability due to their black-box architectures. In contrast, systems that focus on extracting explicit geometric vascular features, such as QUARTZ, offer improved interpretability but require substantial computational infrastructure that may limit their practical deployment [28]. Additionally, systems designed to analyze dynamic retinal features rely on video-based imaging technologies that are not commonly available in routine clinical practice [31]. Furthermore, many current automated systems tend to rely either on complex neural network predictions or on primary geometric vascular measurements alone. This often results in the exclusion of potentially valuable supporting indicators such as color statistics, texture descriptors derived from Gray-Level Co-occurrence Matrix (GLCM) analysis, vascular topology patterns, and image quality indicators.

These gaps highlight the need for a system that balances interpretability, computational efficiency, and practical accessibility. In response to these limitations, the proposed system aims to develop a web-based platform capable of extracting interpretable primary geometric retinal features while strengthening predictive capability through the inclusion of secondary supporting features. By

integrating core vascular biomarkers with complementary contextual indicators, the system provides a hybrid feature extraction approach that remains computationally lightweight and clinically understandable. This design enables accessible and reliable hypertension and cardiovascular disease risk screening suitable for deployment in local primary care centers and remote healthcare environments.

Table 2. Conceptual Mapping Table of the Related Systems

System/ Model	Core Methodology & Input Data	Key Features/ Biomarkers Extracted	Computational & Deployment Needs	Clinical Interpretability
Google AI (Poplin et al.) [14]	Deep Learning <i>(Static Fundus Images)</i>	Implicit (Predicts BP, age, smoking, and MACE directly)	High (Trained on massive UK Biobank/EyePACS datasets)	Low ("Black Box") Bypasses specific geometric retinal features.

QUARTZ System [28]	Automated Feature Extraction <i>(Static Fundus Images)</i>	Primary Geometric (Vessel width, area, tortuosity)	Heavy Requires significant computational resources and dedicated local software.	High Provides explicitly measurable vascular indicators.
Reti-CVD [27]	Deep Learning AI-SaMD <i>(Static Fundus Images)</i>	Implicit (Estimates CAC probability and generalized CVD risk)	Commercial / Proprietary	Low ("Black Box") No detailed physiological explanations or specific microvascular regions shown.
Reti-aging Score [30]	Deep Learning Pipeline <i>(Static Fundus Images)</i>	Implicit (Predicts vascular aging, risk for new-onset hypertension)	N/A	Low ("Black Box") Direct image-to-prediction; lacks isolated geometric validation.

U3D-Net (Panahi et al.) [31]	3D Convolutional Neural Networks (<i>Retinal Video Sequences</i>)	Dynamic/Temporal (Spontaneous Retinal Venous Pulsations / SVPs)	Impractical for Primary Care Relies on uncommon video-based retinal imaging.	Moderate End-to-end classification of temporal vascular behavior.
Web-Based Automated Geometric Vascular Feature Extraction	Hybrid Feature Extraction (<i>Static Fundus Images</i>)	Primary Geometric (Width, Tortuosity) + Secondary Contextual (GLCM Texture, Color, Topology, Quality)	Lightweight & Accessible Web-based platform designed for low-resource primary care.	High Clinically understandable and explicit geometric vascular indicators.

Related Studies

I. Cardiovascular Health Challenges in the Philippines

Cardiovascular diseases (CVDs) remain the leading driver of mortality in the Philippines, with ischemic heart diseases accounting for over 18% of all national deaths in recent years [1], [5]. By 2025, heart disease, cancer, and stroke are projected to remain the leading causes of death, representing a persistent "public health emergency" [3],

[6]. Despite this, the Philippine healthcare infrastructure faces persistent challenges in the distribution and availability of essential diagnostic tools [2], [6]. Because Filipino populations exhibit unique health patterns compared to Western counterparts, there is a critical need for localized, low-cost screening technologies that can circumvent the need for invasive testing [4], [5].

II. The Retina as a Hemodynamic Biomarker

The eye is uniquely positioned as a "window" to the heart, as its microvasculature shares anatomical and physiological traits with the coronary and cerebral systems [9]. This physiological link has given rise to the field of "cardiac-oculomics," where recent comprehensive reviews [14] validate that retinal imaging can identify specific biomarkers such as arteriovenous nicking and vessel density changes, that directly correlate with systemic cardiovascular risks. While static biomarkers such as retinal vessel caliber and branching patterns have long been linked to incident cardiovascular events [13], recent focus has shifted toward dynamic indicators. Spontaneous Retinal Venous Pulsations (SVP) are rhythmic changes in the caliber of the central retinal vein at the optic disc, driven by the pressure gradient between the intraocular and intracranial

compartments [11], [12]. The presence or absence of SVPs provides clinically significant insight into hemodynamic status; for instance, reduced SVP amplitudes are correlated with increased intracranial pressure and cardiovascular instability [10].

III. Deep Learning and the U3D-Net Architecture

To bridge the gap between complex video data and clinical diagnosis, advanced Deep Learning (DL) frameworks are being employed. The U3D-Net is a specialized end-to-end model designed for the autonomous classification of SVPs in retinal videos [15]. Its architecture consists of two modules: an optic disc localizer (often using a fast attention recurrent residual U-Net) and a 3D-convolutional classifier [15]. In rigorous testing, this 3D Inception-based model achieved an accuracy of 84% and a sensitivity of 90%, significantly outperforming traditional time-series classifiers like ConvLSTM in detecting subtle venous pulsations [15]. By extracting both spatial features (vessel structure) and temporal features (pulsatility), these models—particularly 3D Inception and ConvLSTM variants—outperform traditional 2D CNNs in detecting conditions like glaucoma and heart failure [15], [18].

Complementing this, the development of specialized frameworks like the U-Time model has demonstrated that temporal retinal features can be leveraged for automated heart rate estimation and cardiac cycle phase detection directly from fundus video sequences [19]. By utilizing a combination of 2D-CNNs for spatial feature extraction and 1D-CNNs for temporal sequence modeling, these architectures effectively capture the subtle pixel-intensity variations caused by blood flow, achieving a high correlation with traditional ECG and PPG gold-standard measurements [19]. This dual capability—localizing the optic disc while simultaneously quantifying the heartbeat through pixel-intensity analysis—validates the use of Fundus Video Sequences (FVS) as a complete, non-invasive surrogate for systemic cardiovascular monitoring.

IV. Emerging Biomarkers and Non-Invasive Diagnostics

Integration of retinal biomarkers with systemic data is the current frontier of cardiology. Colcombe et al. emphasized that the field is shifting toward "Personalized Medicine," where novel biomarkers—such as Retinal Ischemic Perivascular Lesions (RIPLs) and capillary density mapping—are used to predict specific outcomes like myocardial infarction and stroke [20]. For instance, the use of Optical

Coherence Tomography Angiography (OCTA) has enabled researchers to correlate retinal vessel density with the severity of coronary artery disease [10], [21]. Beyond structural changes, the analysis of blood flow velocity and vessel diameter variations—quantified through automated tracking in videos—provides a real-time assessment of ocular blood flow [22], [23]. Validating this approach, a study from 2023 [11] utilized a video-ophthalmoscope to demonstrate that the timing of vein collapse is strictly phase-locked to the cardiac cycle, occurring 60–220 ms after the R-wave. This confirms that video-based "photoplethysmographic" analysis can serve as a precise, non-invasive proxy for intracranial and systemic pressures. These technological strides facilitate the development of low-cost, portable screening devices using Raspberry Pi or mobile health (mHealth) platforms, making early cardiovascular intervention accessible to underserved regions [18], [24].

V. Multidimensional Feature Integration for Dynamic Robustness

Current literature indicates that the efficacy of automated systems for hypertensive retinopathy is traditionally based on primary vascular biomarkers; however,

recent studies emphasize incorporating "support" features to mitigate the inherent stochasticity of fundus photography [32], [33]. While Arteriolar-to-Venular Ratio (AVR), tortuosity, and fractal dimensions provide core morphological indicators, these systems are often susceptible to acquisition noise and inhomogeneous lighting [34]. Consequently, contemporary studies propose a multidimensional feature space using spectral, textural, and topological descriptors as contextual constraints. These features function as a stabilizing framework within automated systems, ensuring decision-making remains robust even when primary geometric markers are obscured [35].

Central to this systemic optimization is the use of spectral and chromatic statistical analysis to quantify sub-visual shifts in vessel wall reflectivity. In chronic hypertension, the arteriolar light reflex widens, leading to clinical "copper-wiring" or "silver-wiring" [36]. By calculating mean intensity, variance, and local contrast, modern deep learning frameworks detect pathological changes in tone frequently omitted by shape-based algorithms [37], [38]. Furthermore, Gray-Level Co-occurrence Matrix (GLCM) analysis allows for second-order statistical characterization of retinal topography [39]. By quantifying

visual "grain" through metrics like entropy and homogeneity, these systems identify localized structural irregularities, such as early cotton-wool spots, which provide critical evidence of systemic vascular stress [40], [41].

VI. Topological Integrity and Quality Assessment in Automated Frameworks

The deployment of automated diagnostic tools in web-based environments introduces specific technical challenges regarding data reliability and system accuracy. Recent studies highlight "quality and reliability indicators" as essential computational gatekeepers within these frameworks [42]. These metrics evaluate the mathematical plausibility of extracted vessel maps by analyzing segmentation density and continuity [43]. In cases of suboptimal image quality, these system-level indicators allow the model to adjust confidence intervals or flag untrustworthy measurements, thereby reducing false positives in heterogeneous clinical datasets [44], [45].

Beyond image quality, the structural layout of the microvascular tree, represented through vessel topology, offers a global perspective on systemic health [18]. By treating the retinal vasculature as a complex topological graph, related systems quantify "capillary rarefaction," or the loss of microvascular complexity, which is a hallmark of sustained hypertension [46]. These descriptors include the density of bifurcation points and the frequency of terminal vessel endings, providing a measure of overall network connectivity [47], [48]. Integrating these descriptors ensures that the system assesses the integrity of the entire vascular architecture rather than vessels in isolation [49]. Collectively, these multidimensional studies and systems bridge the gap between simple geometric measurement and holistic, clinical-grade cardiovascular risk assessment [29], [50].

CHAPTER 3 RESEARCH DESIGN AND METHODOLOGY

Description of the Proposed Study

The proposed system operates through a comprehensive processing pipeline designed to transform raw retinal images into clinically actionable intelligence. Upon upload, static fundus images undergo validation and preprocessing, including noise reduction and contrast enhancement, to optimize vessel visibility. Deep learning-based vessel segmentation then generates binary masks from which three primary geometric biomarkers are extracted: the Arteriolar-to-Venular Ratio (AVR) quantifying generalized arteriolar narrowing, vessel tortuosity measuring vascular curvature associated with hemodynamic stress, and vascular fractal dimension capturing the geometric complexity of microvascular branching. To enhance prediction reliability, the system additionally extracts secondary supporting features including color statistics, Gray-Level Co-occurrence Matrix (GLCM) texture features, vessel topology metrics, and segmentation quality indicators that provide contextual constraints without replacing the primary biomarkers. These multidimensional features are integrated into a feature vector and processed by a machine learning-based hypertension prediction engine, which generates both a

quantitative probability score and a categorical classification label. The system subsequently performs CVD risk stratification, classifying patients into Low, Intermediate, or High-risk categories based on composite vascular analysis.

All analytical outputs are delivered through an intuitive web-based reporting platform designed for seamless clinical integration. The interface visualizes extracted vascular features, displays hypertension probability scores alongside CVD risk classifications, and generates clinician-friendly reports that translate complex geometric measurements into accessible, interpretable formats. By leveraging cloud-based architecture, the system enables remote access and scalable deployment across diverse healthcare institutions—from tertiary hospitals to rural health units—democratizing advanced retinal vascular analysis traditionally requiring specialized equipment and expert interpretation. This web-based delivery model empowers primary care physicians and community health workers with sophisticated decision-support capabilities, aligning with the goals of Universal Health Coverage and preventive cardiovascular care in the Philippines.

Methods and Proposed Enhancements

This study adopts a modular methodology so each stage can be independently validated and improved without redesigning the entire system. The workflow starts from standardized retinal image intake, proceeds through quality-aware vessel analysis, and ends in calibrated screening output. The implementation is intentionally structured around interpretable vascular markers to support clinical plausibility, while maintaining computational practicality for web deployment [51], [16], [52].

The methods are organized into: data acquisition, data preprocessing, data augmentation, reliability scoring, feature extraction, model evaluation, model integration, and system testing. Each module contributes a specific function to ensure reproducible and auditable screening behavior. This design is aligned with the principle that clinically meaningful retinal analysis systems should not rely solely on a single black-box prediction pathway, but should instead preserve measurable intermediate structures that can be examined, validated, and improved over time [51], [53], [52].

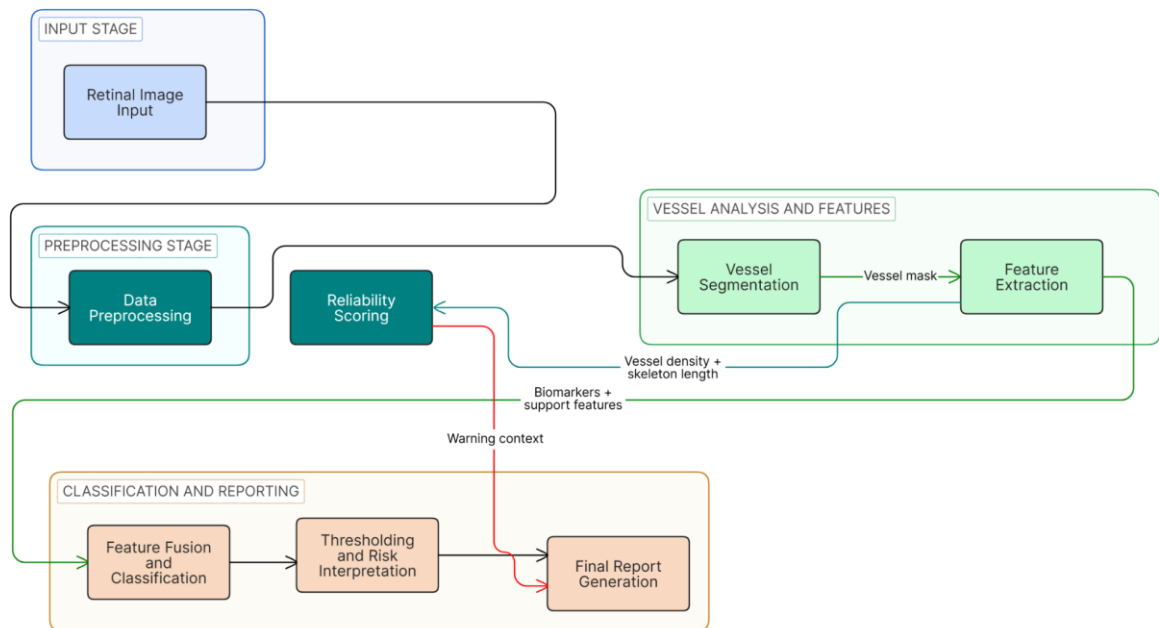


Figure 2. Retinal Analysis Pipeline Overview

This figure shows the overall retinal screening flow: image input, preprocessing, reliability screening, vessel segmentation, feature extraction, classification, and final report generation. It should emphasize that the pipeline is sequential and modular.

Data Acquisition

The current pipeline accepts static color fundus images from curated datasets used for training, feature extraction, and evaluation. The implemented workflow is centered on offline processing of retinal images stored in standard

image formats, after which preprocessing and downstream analysis are applied in a fixed sequence.

For model development and testing, the datasets used in this study were acquired from two publicly available sources: the CGI-HRDC 2023 Hypertensive Retinopathy Diagnosis Challenge dataset and the Fundus Image Dataset for Vessel Segmentation (FIVES) [54], [55]. The CGI-HRDC source provides two related classification tasks, namely hypertensive classification and hypertensive retinopathy classification, with each task containing 712 fundus images in the training set and 288 images in the hidden test set. These datasets are valuable for the classification stage of the study because they directly correspond to hypertension-related retinal assessment. Meanwhile, the FIVES dataset contains 800 high-resolution color fundus photographs with expert vessel annotations at the pixel level, making it suitable for vessel segmentation model development and for validating the extraction of vascular geometry from retinal images. In this way, the acquired datasets support both major parts of the pipeline: vessel segmentation and hypertension-oriented classification.

For the intended web-based deployment, image input may later be acquired through user-uploaded static fundus

photographs. Unlike the development datasets, such inputs would reflect real-world variation in device, resolution, framing, and illumination.

To reduce domain drift, the dataset composition assumes centered retinal fields, visible vessels, and analyzable vessel continuity. Image-label alignment and partition boundaries are also verified to avoid leakage and preserve valid evaluation.

The acquisition strategy is important because retinal screening systems are highly sensitive to inconsistencies in framing, illumination, and anatomical visibility. Images with strong truncation, severe blur, or low vessel visibility can distort segmentation behavior and weaken vascular marker estimation. For this reason, the input stage is not treated as a passive upload process; rather, it functions as the first control point in preserving the validity of downstream analysis [56], [11], [53], [57], [58], [59].

Inclusion criteria are as follows:

1. Adequate field of view with visible vascular structures.

2. Sufficient illumination and contrast for vessel extraction.

No severe blur, occlusion, or truncation that invalidates vessel analysis.

Data Preprocessing

The preprocessing stage standardizes image scale, contrast, and pixel distribution before vessel segmentation. It reduces inter-camera variability and prepares the images for reliable structural analysis [60], [61], [62].

In the implemented pipeline, preprocessing follows a fixed sequence so that every image received by the model is converted into a consistent numerical and spatial representation. The preprocessing procedures used in the current system are as follows:

1. Fundus Image Standardization

The first preprocessing step resizes each retinal image to a square format while preserving the original aspect ratio. In the current implementation, images are resized and padded to 512 x 512 pixels so that vessel geometry is not distorted by arbitrary stretching.

Padding is applied on a black canvas so the final input

remains spatially aligned for the segmentation network. This is important because the segmentation model expects a fixed input size, yet the source datasets contain images with different original resolutions and field coverage

2. Contrast Enhancement and Normalization

After spatial standardization, contrast-limited adaptive histogram equalization (CLAHE) is applied to improve local vessel visibility, especially in low-contrast regions. In the current implementation, the enhancement is applied through the luminance channel so that vessel-background contrast is improved without introducing unnecessary color distortion. After enhancement, each image is normalized channel-wise using predefined mean and standard deviation values so that pixel intensities are placed on a stable scale for model inference. This process reduces numerical instability and improves the consistency of model behavior across heterogeneous image sources.

3. Segmentation Mask Preprocessing

For segmentation training data, the corresponding vessel masks also undergo preprocessing before they are

used by the model. Each mask is converted to grayscale, if necessary, resized and padded to the same 512 x 512 format, and binarized using a fixed threshold so that vessel pixels are represented consistently. This step is necessary because segmentation learning depends on direct alignment between the processed input image and the processed vessel mask.

These operations are especially relevant in web-based screening settings, where uploaded images may come from devices with different capture characteristics. By standardizing both the images and, when applicable, the segmentation masks, the system reduces unwanted variation before vessel analysis begins.

The preprocessing transformation is summarized by the following normalization form.

$$\tilde{I}_c(x, y) = \frac{I_c(x, y) / 255 - \mu_c}{\sigma_c}$$

Equation 1. Image Normalization Equation

This equation shows how each color channel is standardized to reduce camera-dependent intensity variability and improve model stability.

The use of normalization in this context is not intended to alter the retinal anatomy, but to place pixel intensities in a controlled numerical range so segmentation and downstream inference remain stable. In practice, this supports both training convergence and inference consistency, particularly when the model receives images from varied clinical or semi-clinical acquisition settings.

Data Augmentation

Data augmentation is used as a selective robustness strategy rather than as a transformation applied to every pipeline stage. In the implemented pipeline, augmentation is actively used during vessel segmentation training on the FIVES dataset so that the U-Net is exposed to plausible spatial and photometric variation [60], [61], [62].

For segmentation training, the current implementation applies random horizontal flips, random vertical flips, random 90-degree rotations, and occasional brightness and contrast adjustments before the preprocessed image-mask pair is passed into the model. These transformations are applied jointly to the retinal image and its vessel mask so that anatomical alignment is preserved during learning. By doing so, the model is encouraged to learn vessel structure more

robustly rather than overfitting to a narrow spatial presentation of the training set.

The pipeline also uses test-time augmentation during segmentation inference. It predicts vessel masks from the original image, a horizontally flipped image, a vertically flipped image, and a doubly flipped image, then averages the resulting probability maps before thresholding.

Although the classification dataset loader includes optional spatial augmentation support, the current main training workflow does not rely on a separate augmentation-heavy classifier stage. Thus, data augmentation in this study is mainly a segmentation-oriented robustness mechanism.

Reliability Scoring

A quality and reliability stage is applied before final prediction. The current implementation uses vessel-density and skeleton-length plausibility checks to flag low-confidence masks.

This stage helps prevent unreliable segmentation outputs from being treated as equally trustworthy during feature extraction and evaluation. At present, low-quality

cases are handled through warnings and report logging rather than a strict automatic retake policy [56], [57], [58].

Feature Extraction

Feature extraction begins with vessel segmentation and proceeds to geometric, structural, and support descriptors used for screening inference. A U-Net-based model first predicts vessel probability maps, which are then threshold into binary masks. This segmentation stage is the structural foundation of the pipeline because all later biomarkers depend on it [60], [61], [62].

Once the vessel map is obtained, the system extracts three core biomarkers from segmented vessel structures:

1. Arteriolar-to-Venular Ratio (AVR)
2. Vessel Tortuosity
3. Vascular Fractal Dimension

These biomarkers were selected because they directly support the study objective of using retinal vascular geometry for hypertension-related screening [11], [53], [59].

$$AVR = \frac{CRAE}{CRVE + \epsilon}$$

Equation 2. Arteriolar-to-Venular (AVR) Equation

This equation shows the vessel caliber ratio used to quantify arteriolar narrowing relative to venular caliber. In the current implementation, AVR is estimated from segmented vessel widths after artery-vein separation and summary caliber computation [53], [59].

$$\tau_b = \frac{L_b}{D_b + \epsilon}$$

Equation 3. Vessel Tortuosity Equation

This equation shows branch-level tortuosity as the ratio between arc length and chord length. Branch-level estimates are aggregated into summary descriptors to reduce sensitivity to outlier segments [11], [59].

$$FD = -\frac{d \log N(s)}{d \log s}$$

Equation 4. Fractal Dimension Equation

This equation shows vessel network complexity using box-counting behavior across spatial scales. It complements caliber- and tortuosity-based measures by preserving a network-level view of retinal structure [11], [53].

To improve robustness, the model also extracts support features:

1. Vessel density and branching descriptors
2. Color statistics from vessel and background regions
3. Texture statistics using GLCM-based descriptors
4. Reliability indicators tied to segmentation

plausibility

These support features strengthen prediction when geometric markers are partially unstable. They are used as contextual stabilizers rather than standalone clinical findings [51], [52].

After extraction, the primary biomarkers and support features are fused into one feature vector, normalized, and passed to the classifier. The classifier outputs a screening probability used for risk stratification.

This stage preserves traceability from measured vascular features to final prediction. Optional post-hoc calibration is also applied when the validation-stage calibration step is successfully saved and reused.

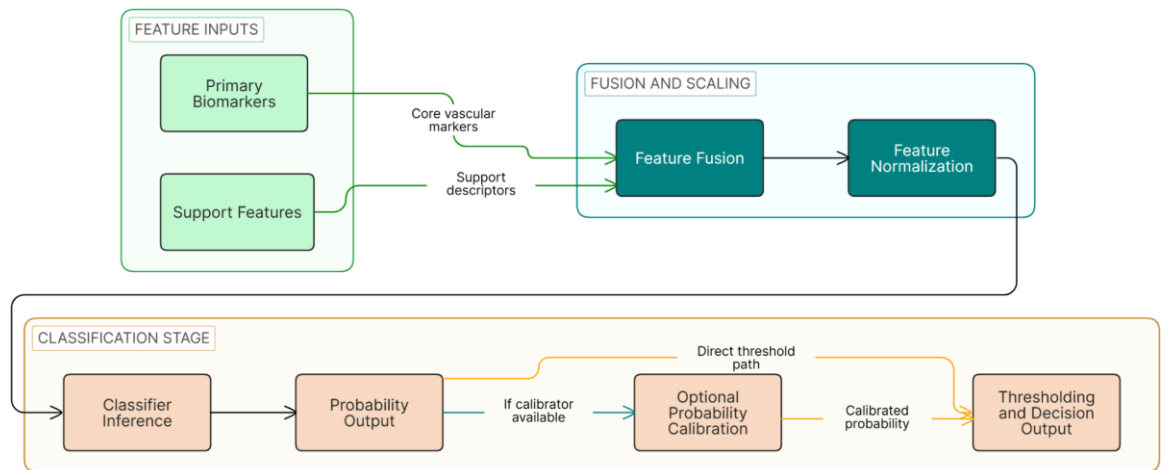


Figure 3. Feature Fusion and Classification Module

This figure shows how the extracted primary biomarkers and support features are combined before normalization, classifier inference, and probability calibration. It should emphasize that prediction is based on structured vascular descriptors rather than the raw retinal image.

During training, classification error is minimized using cross-entropy.

$$\mathcal{L}_{CE} = - \sum_{i=1}^K y_i \log(\hat{y}_i)$$

Equation 5. Cross-Entropy Loss Formula

This equation shows how the model penalizes mismatch between predicted class probabilities and ground-truth labels.

The final screening decision is produced by applying a calibrated threshold to the predicted probability. The output combines class prediction, score interpretation, and reliability context.

$$\hat{y} = \mathbb{1}[\hat{p}_{cal} \geq t^*]$$

Equation 6. Screening Decision Threshold Equation

This equation shows how continuous risk probability is converted into a binary screening decision. The threshold term t^* is selected from validation behavior rather than fixed arbitrarily.

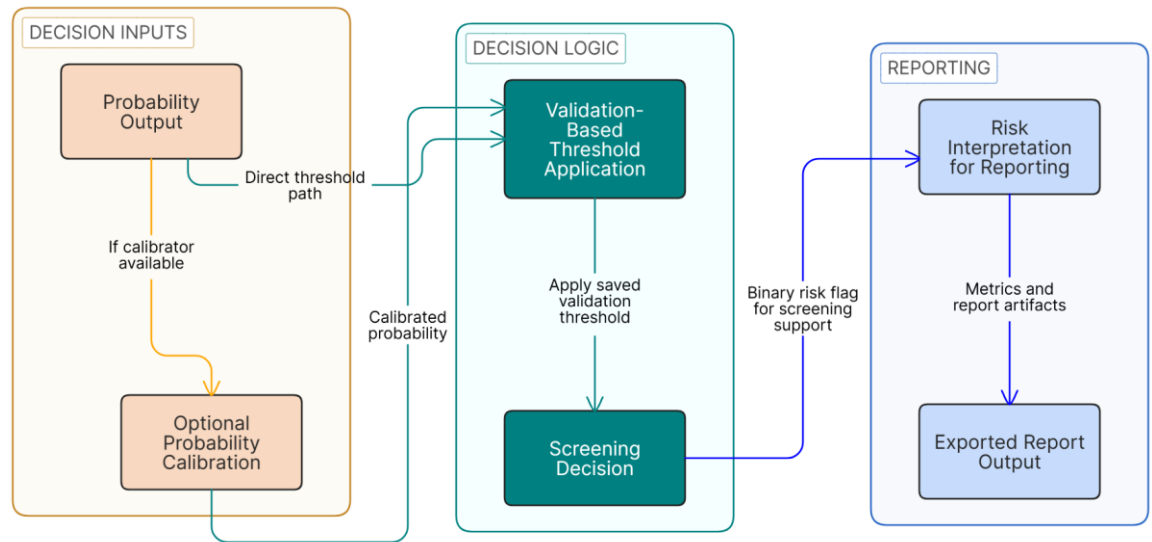


Figure 4. Risk Stratification and Report Logic

This figure shows how the classifier probability is optionally calibrated, compared against a validation-derived threshold, converted into a binary hypertension screening decision, and translated into a conservative risk interpretation for exported reporting. In the current implementation, this stage supports threshold-based screening output rather than formal multi-stage hypertension grading or a quantitative cardiovascular risk score.

Model Evaluation

Model performance is reported using standard classification metrics across validation and held-out test sets. Evaluation includes both threshold-dependent and threshold-independent views so that operating-point selection remains clear [16], [52].

$$F1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Equation 7. F1-Score Equation

This equation shows the harmonic balance between precision and recall for screening performance evaluation.

Additional reported metrics include accuracy, sensitivity, specificity, and AUC, with threshold analysis for deployment alignment.

Among these metrics, F1-score is useful as it captures the balance between missed detections and incorrect positives in a single value. However, the full evaluation should still be interpreted together with sensitivity, specificity, and calibration, especially when the operational goal is risk flagging rather than generic classification.

Model Integration

The operational workflow of the implemented pipeline is:

1. Datasets and paths are verified.
2. Preprocessing and vessel segmentation are executed.
3. Geometric and support features are extracted from the segmented masks.
4. The classifier computes class probabilities and the evaluation pipeline apply threshold selection and optional calibration.
5. Evaluation summaries, checkpoints, feature tables, and report files are exported.

The present repository does not yet implement a full browser-based request-response interface or a non-persistent upload policy. Those deployment behaviors belong to the intended web application layer rather than the current pipeline scripts.

The current deployment path is structured as a reproducible pipeline: deterministic preprocessing, monitored segmentation quality, structured feature extraction, threshold-based classification, and exported evaluation artifacts.

The intended web-based design may improve feasibility for screening settings because the main computational burden can remain in the backend while the user-facing interface stays simple and report-oriented [16].

Within the implemented scripts, the trained segmentation and classification components are executed as one continuous pipeline during feature extraction and evaluation. Retinal images are first preprocessed, then segmented, converted into geometric and support features, and finally passed to the classification stage to generate probability outputs, threshold-based predictions, and evaluation reports.

System Testing

The study tests the complete system by verifying each major pipeline phase and then evaluating the end-to-end output behavior. Testing begins with dataset and path verification, followed by vessel segmentation training, feature extraction, classifier training, and evaluation report generation.

System testing also includes review of segmentation plausibility, exported feature tables, checkpoint outputs,

and evaluation summaries so that intermediate failures can be traced more easily.

Proposed Enhancements

Building on the methods presented in this study, the researchers propose several enhancements to strengthen the reliability, practicality, and real-world utility of the retinal screening system. The first is quality-aware inference gating, in which low-quality retinal images are no longer handled only through warnings, but through a stricter decision policy of proceed, proceed with warning, or retake required. This would better align the system with retinal image quality assessment literature and reduce the risk of generating high-confidence outputs from insufficient visual evidence [56], [57], [58].

Another proposed enhancement is the use of lightweight segmentation models for deployment, particularly for web-based and low-resource screening settings. Candidate models should be evaluated not only by speed, but also by their ability to preserve biomarker fidelity for measures such as AVR, tortuosity, and network complexity [61], [62].

The researchers further propose a more robust hybrid feature design in which the contribution of geometric and

support features is adjusted according to image reliability. A future enhancement would be to apply quality-conditional weighting so that support descriptors contribute more strongly when geometric measurements are uncertain, while explicit vascular biomarkers remain dominant when segmentation confidence is high. A related enhancement is refinement of calibration and threshold optimization so that decision boundaries reflect screening priorities, especially sensitivity and acceptable false-positive burden.

Another enhancement is the development of explainability-centered reporting and stronger workflow integration for real screening environments. Future reports can be improved by summarizing feature-level reasoning, such as AVR direction, tortuosity context, feature-group contribution, and quality-related caveats. Additional readiness indicators such as turnaround-time consistency, reliability monitoring, and usability measures may also strengthen deployment credibility [16], [52].

Through these enhancements, the proposed system can move beyond a technically valid retinal analysis pipeline and become a more dependable, interpretable, and deployment-ready screening platform. These enhancements do not replace

the core methodology, but extend it toward a more mature and clinically relevant implementation.

Components and Design

System Architecture

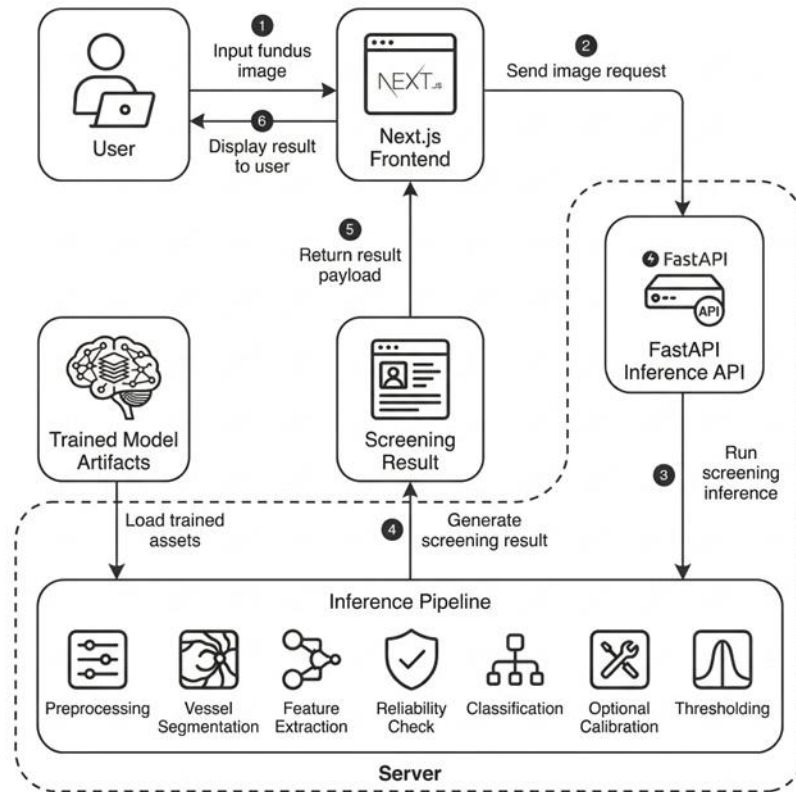


Figure 5. System Architecture

As depicted in Figure 5, the proposed system employs a web-based retinal screening architecture that processes uploaded fundus images and returns a screening result to the user. The process begins when the user submits a retinal fundus image through the Next.js frontend (1), which serves as the browser-facing interface of the system. The frontend

then forwards the uploaded image to the FastAPI inference API through an image request (2). Upon receiving the request, the FastAPI backend triggers the server-side inference pipeline (3), which performs the sequential stages of preprocessing, vessel segmentation, feature extraction, reliability checking, classification, optional calibration, and thresholding. To support this live inference process, trained model artifacts are loaded into the pipeline as server-side assets. After processing, the pipeline generates the screening result (4), which is returned as a result payload to the Next.js frontend (5). Finally, the frontend presents the screening output back to the user (6). As shown in the architecture, the server-side infrastructure contains the FastAPI backend, the trained model artifacts, and the inference pipeline, while the user-facing side consists of the user and the Next.js frontend. This overall design enables inference-only retinal screening without requiring authentication, database-backed storage, or permanent upload retention.

Software Architecture

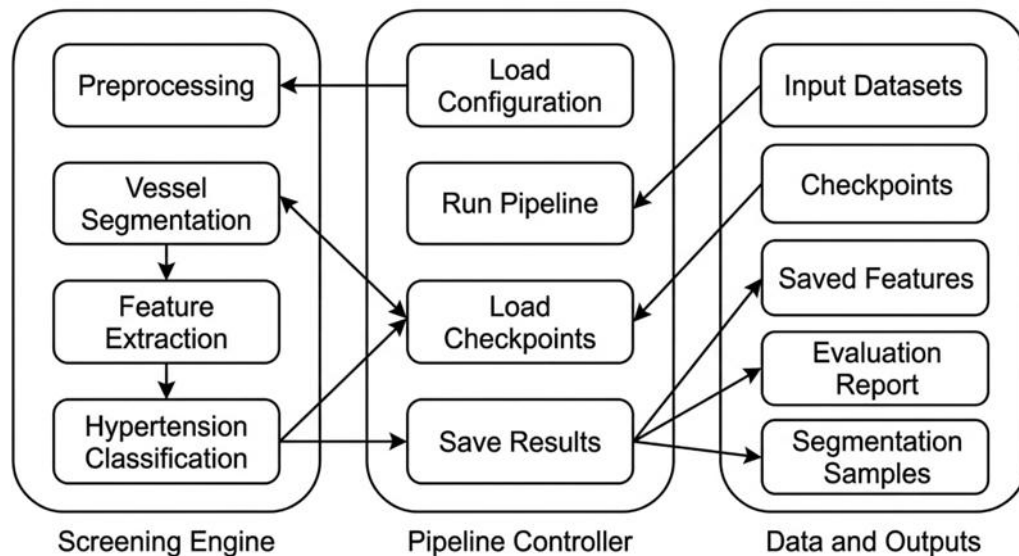


Figure 6. Software Architecture

As depicted in Figure 6, the proposed system employs a modular software architecture for retinal fundus image screening and hypertension prediction. The process begins with the loading of the input datasets (1), which are accessed and coordinated by the Pipeline Controller through the configuration stage (2) and the pipeline execution stage (3). After the pipeline is initiated, the fundus images are subjected to preprocessing (4) to prepare them for subsequent analysis. The preprocessed images are then forwarded to the vessel segmentation stage (5), where the retinal vasculature is isolated for geometric analysis. To support this analysis, trained model parameters are loaded through the checkpoint-loading module (6), which provides

the learned weights required by the segmentation and classification stages. Once vessel structures are obtained, the system performs feature extraction (7) to derive vascular characteristics from the segmented retinal images, and these extracted features are then passed to the hypertension classification stage (8) for prediction. The resulting outputs are consolidated by the result-saving module (9), which stores the processed artifacts as saved features (10), evaluation reports (11), and segmentation samples (12). As shown in the architecture, the overall software framework is divided into three major groups: the Screening Engine, which performs the main analytical operations; the Pipeline Controller, which manages execution, configuration, checkpoint loading, and result saving; and the Data and Outputs module, which provides the datasets and stores the persistent artifacts generated by the system.

Procedural Design

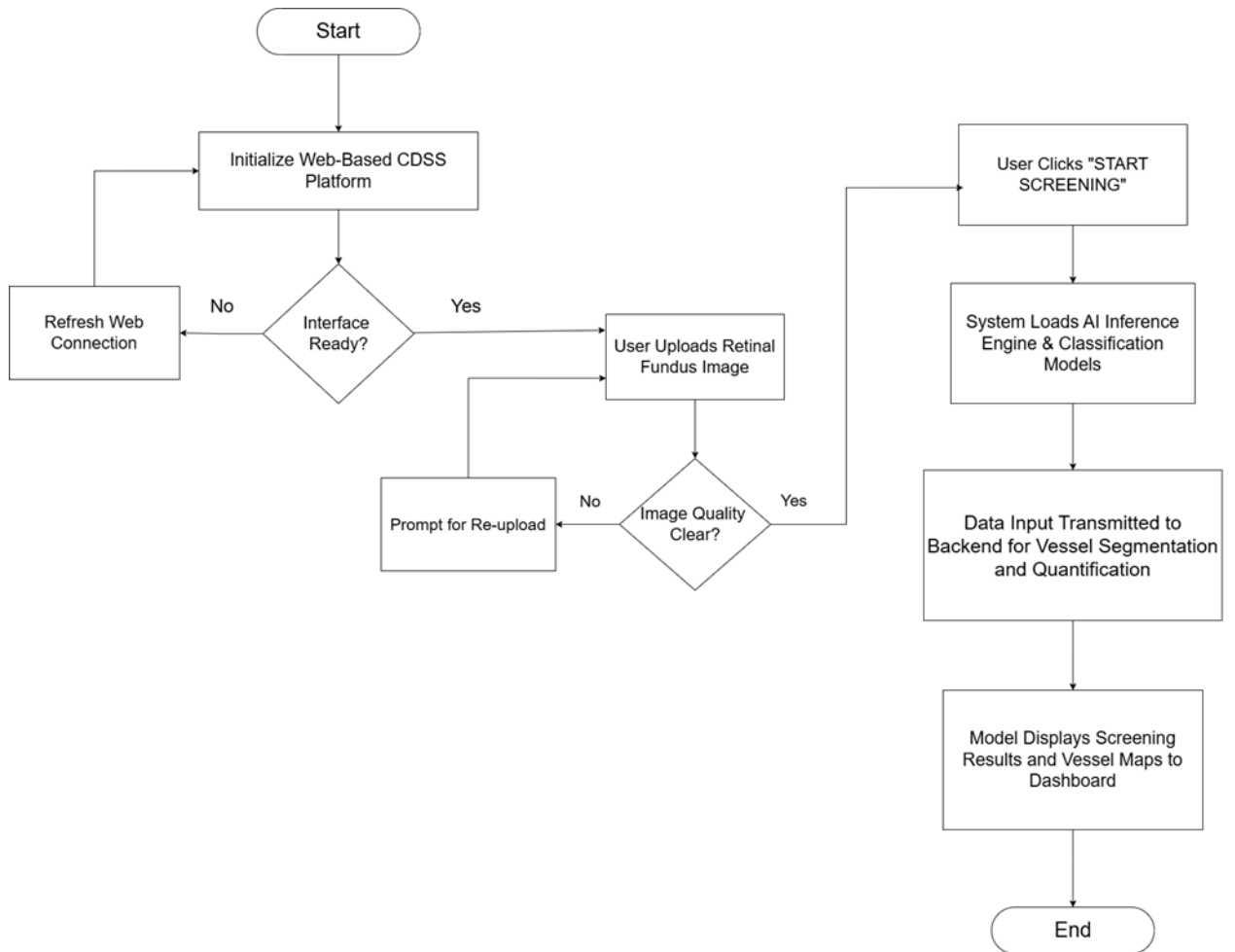


Figure 7. System Procedural Design

This figure illustrates the operational workflow of the Web-Based Automated Geometric Vascular Feature Extraction From Static Fundus Images For Hypertension Detection And CVD Risk Stratification. The workflow begins with the initialization of the web interface to establish a stable environment for data entry. Should the connection fail to stabilize, the system requires the user to reset the session before continuing. Once the platform is fully accessible,

the clinician proceeds by importing a static retinal fundus image. If the system detects that the image quality is suboptimal for analysis, it triggers a notification for the user to perform a re-upload. Following the confirmation of a valid input, the user engages the "START SCREENING" function. This action prompts the system to activate the AI Inference Engine along with the necessary diagnostic models. During this stage, the image data is transferred to the server-side for automated vessel mapping and the calculation of specific ocular biomarkers. The resulting analysis interface and corresponding vascular visualizations are subsequently routed back to the analysis interface, signifying the completion of the automated screening cycle.

Object-Oriented Design

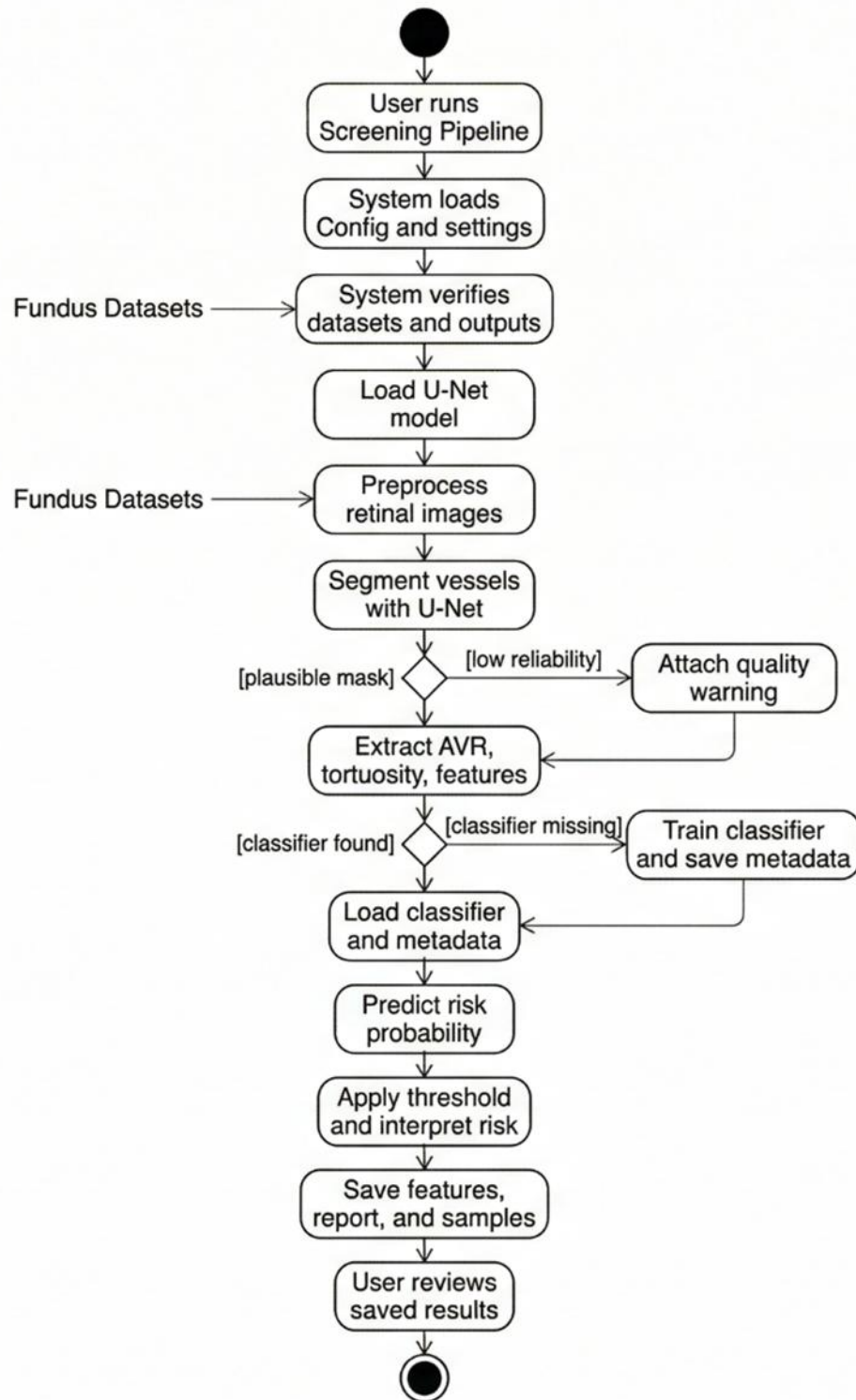


Figure 8. Activity Diagram

Figure 8 presents the activity diagram of the proposed retinal hypertension screening pipeline. The workflow begins when the user initiates the screening process, prompting the system to load the configuration parameters, execution settings, file paths, and required output directories. After initialization, the system verifies the availability of the retinal datasets and supporting artifacts needed for execution. Once the initial checks are completed, the retinal images are preprocessed through resizing, padding, enhancement, and normalization to ensure consistent input quality. These preprocessed images are then passed to the vessel segmentation stage, where the U-Net generates vessel masks that serve as the foundation for subsequent analysis. The diagram also reflects the reliability handling mechanism of the system, wherein low-plausibility masks are not immediately discarded but instead flagged with a quality warning so that the analysis may continue with caution.

From the segmented vessel structures, the system extracts the primary vascular biomarkers and supporting descriptors, including arteriolar-to-venular ratio (AVR), vessel tortuosity, fractal dimension, vessel density, and branching-related features. The pipeline then checks whether a classifier artifact is available. If none exists, the classifier is trained using the extracted feature set and the resulting model and metadata are saved; otherwise, the saved classifier and associated metadata are loaded for inference. The classifier then produces a risk probability, which is transformed into a screening decision through threshold-based interpretation. Finally, the system stores the extracted features, segmentation samples, checkpoints, and evaluation report, after which the user reviews the generated screening results.

Methodology

System Development Life Cycle

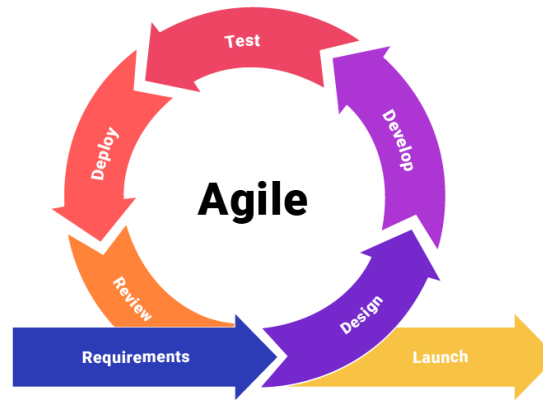


Figure 9. Agile Development Life Cycle [44]

The researchers utilized the Agile System Development Life Cycle to achieve the project objectives. Agile model is a combination of iterative and incremental process models with focus on process adaptability and customer satisfaction by rapid delivery of working software products. The following are the phases in the Agile System Development Cycle:

1. Requirements Gathering

In this phase, the researchers conducted sprints, exploring the existing landscape of Automated Geometric Vascular Feature Extraction from Static Fundus Images. Various paper consultations and exploration tackled similar or related concepts and implementations of

oculomics, hypertension detection, and CVD risk stratification systems. To ensure clinical validity, the researchers consulted with domain experts from Iloilo Doctors' Hospital and St. Paul's Hospital Iloilo. Additionally, publicly available fundus image datasets were gathered from the web to serve as the foundational training data. The researchers traversed algorithms, models, methodologies, research gaps, and state-of-the-art innovations in the field. Expected deliverables is the initial prototype scope based on feasibility assessment.

2. Design

This phase involves sprints in designing a modular system architecture that integrates: Data Acquisition modules to handle static retinal fundus image inputs sourced from the web datasets; Data Preprocessing modules to facilitate image processing techniques including noise reduction and vessel segmentation; Feature Extraction to compute primary geometric vascular biomarkers (such as Arteriolar-to-Venular Ratio, Vessel Tortuosity, and Vascular Fractal Dimension) alongside secondary GLCM textural features.

3. Development

During this phase, the actual coding and construction of the system take place through iterative sprints. The researchers focused on building the ensemble classifier module for automated hypertension detection and CVD risk stratification. This phase also includes the sprint development of the Web-based platform, linking the predictive models to a web server to provide remote retinal image analysis, visualization, and reporting capabilities. Continuous refactoring and integration through sprint reviews are done. This phase's expected deliverables are the incremental code releases after each sprint and the fully integrated module after multiple sprint cycles.

4. Testing

The testing phase involves rigorous testing through unit modules and integration testing to ensure that each module functions correctly and interacts seamlessly. Currently, the researchers have executed the first iteration of testing using a split from the web-sourced dataset. The initial ensemble model evaluation yielded a 62.61% accuracy and a 73.41% AUC-ROC, demonstrating high sensitivity (88.67% recall) but

low specificity (37.03%) at the initial 0.28 validation threshold. Because the model is still imperfect and prone to over-predicting positive cases, it is undergoing active Agile refinement. This includes optimizing the decision threshold to the Youden index (0.55) to balance precision and recall, as well as feature pruning guided by correlation analysis. In later iterations, testing will transition from the web-sourced data to a local clinical dataset provided by the consulted domain experts from Iloilo Doctors' Hospital and St. Paul's Hospital Iloilo. This localized testing ensures the model's accuracy, robustness, and generalizability to the local patient demographic before final rollout.

5. Deployment

During this phase, the technical transition from a local development environment to a live staging server takes place. The system is optimized for web-based cloud deployment to ensure remote access, scalability, and balanced trade-offs between performance and computational efficiency. The web platform, database, and machine learning models are configured on the hosting infrastructure to ensure the system is stable,

secure, and ready to handle incoming static fundus images.

6. Review

In this phase, before the system is officially released, the researchers focus on evaluating the successfully deployed system. Performance metrics of the web architecture and the integrated model are gathered to identify technical areas for system improvements. Continuous refinement through sprint reviews and retrospectives will be done to ensure that the system meets the necessary clinical standards, user needs, and performance expectations previously outlined by the domain experts. Any final bug fixes or threshold adjustments are finalized here.

7. Launch

This final phase focuses on the actual rollout of the evaluated system to the target audience. An initial beta launch will be conducted, granting system access to selected users and the consulted domain experts from Panay Eye Center and St. Paul's Hospital Iloilo. User Acceptance Testing (UAT) is formally conducted in this stage, allowing the healthcare professionals to utilize the web platform in a real-world setting. This clinical validation serves to test the system's viability as a clinical decision support tool, and the real-world feedback gathered here will inform future iterations and model retraining.

Through this approach, with frequent sprints and stakeholder involvement, ensures that the final system will be robust, efficient, and capable of adapting to future requirements.

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