

# Smart Diagnostic System for Blood Vessel Blockage Using Non-Invasive Methods (Without Angiography)

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**Abstract**—Cardiovascular disease is still the cause of death globally. Sudden heart problems happen because of blocked blood vessels usually due to atherosclerosis. The best tests we have now like angiography are invasive use a lot of radiation are costly and not suitable for regular check-ups, especially in rural areas where medical resources are limited.

This study introduces a non-invasive diagnostic system that uses AI. It combines Photoplethysmography (PPG) infrared imaging and Doppler ultrasound with a deep learning model hosted in the cloud. The system collects data from sensors in real-time cleans it up to remove errors and sends it securely to the cloud for analysis to detect blockages.

The system we propose is designed to be affordable, able to handle a lot of users and easy to use in healthcare settings. By using non-invasive technology, AI and cloud computing it aims to help with early heart screenings make diagnoses more accessible and reduce the need, for invasive tests.

**Index Terms**—Non-Invasive Diagnostics, Blood Vessel Blockage, Cardiovascular Disease, Photoplethysmography, Doppler Ultrasound, Thermal Imaging, ensemble Deep Learning, AI in Healthcare.

## I. INTRODUCTION

Cardiovascular disease is one of the reasons people die all around the world. When we have atherosclerosis it slowly makes our arteries smaller. Reduces blood flow to important parts of our body like the heart and brain. If we can find out about blocked arteries early we can do something about it. Lower the risk of death.

Now the best way to find out if we have a blockage is with a coronary angiography. But this method is not very nice because it is invasive it costs a lot of money. It is not good for people who live in rural areas or places with limited resources.

We have made some progress with ways to sense what is going on in our body store information on the internet and use computers to learn from data. These new developments give us a chance to make a system that can diagnose problems without hurting us. This paper is about a system that uses

devices like PPG, thermal imaging and Doppler ultrasound along, with a type of computer program called ensemble to detect blockages in our arteries. The system is called a Smart Diagnostic System. It uses deep learning to figure out if we have any blockages. Cardiovascular disease and blockages are the focus of this Smart Diagnostic System.

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## II. LITERATURE REVIEW

### A. Physiological Basis of Vascular Blockage

Blood vessel blockage primarily occurs due to atherosclerosis, a condition in which cholesterol, calcium, and fatty substances accumulate along arterial walls. These deposits gradually narrow blood vessels and restrict blood flow to vital organs such as the heart and brain. Reduced blood circulation can result in ischemia, myocardial infarction, stroke, and other severe cardiovascular complications. According to the World Health Organization (WHO), cardiovascular diseases are responsible for nearly 17.9 million deaths annually worldwide [1].

Hemodynamic changes caused by arterial stenosis affect blood velocity, arterial elasticity, pulse wave morphology, and peripheral perfusion. These physiological changes can be observed using non-invasive sensing modalities such as Photoplethysmography (PPG), Doppler ultrasound, and infrared thermal imaging. The combination of these sensing techniques enables early detection of abnormal vascular conditions before complete blockage occurs.

### B. Photoplethysmography (PPG)

Photoplethysmography is a non-invasive optical sensing technique used to measure changes in blood volume during the cardiac cycle. A typical PPG sensor consists of a light source and a photodetector that capture variations in reflected or transmitted light through biological tissues. These variations

produce pulse waveforms that contain valuable cardiovascular information [2].

Researchers have shown that features extracted from PPG signals, including pulse transit time, augmentation index, systolic peak amplitude, and pulse width, are closely associated with arterial stiffness and vascular abnormalities. Owing to their low cost and continuous monitoring capability, PPG sensors are widely employed in wearable devices and healthcare applications [3].

Several studies have demonstrated that machine learning and deep learning algorithms can improve cardiovascular disease prediction using PPG signals. Signal preprocessing techniques such as filtering, normalization, and motion artifact removal significantly enhance diagnostic performance.

### C. Infrared Thermal Imaging

Infrared thermal imaging is a non-contact diagnostic method that measures temperature distribution patterns on the human body. Since blood circulation influences skin temperature, regions affected by vascular blockage often exhibit abnormal thermal patterns compared to healthy tissues [4].

Thermal imaging has found applications in detecting diabetic foot ulcers, breast cancer, inflammation, and peripheral vascular disorders. Recent advances in thermal camera technology have enabled the development of portable and affordable thermal imaging systems suitable for healthcare applications.

Artificial intelligence techniques integrated with thermal imaging improve diagnostic accuracy by automatically extracting discriminative temperature features. Convolutional Neural Networks (CNNs) have demonstrated promising results in medical image classification tasks and thermal pattern analysis.

### D. Doppler Ultrasound

Doppler ultrasound is a widely used non-invasive technique for measuring blood flow velocity using the Doppler effect. Frequency shifts generated by moving blood cells are analyzed to evaluate vascular conditions and identify arterial narrowing [5].

Clinical parameters such as peak systolic velocity, end-diastolic velocity, pulsatility index, and resistive index are commonly used to assess vascular abnormalities. Doppler ultrasound has been extensively applied in the diagnosis of carotid artery disease and peripheral arterial disorders.

Recent technological developments have enabled compact Doppler sensors to be integrated with embedded systems and cloud platforms. Automated signal analysis using artificial intelligence reduces dependence on expert interpretation and improves diagnostic efficiency.

### E. Deep Learning for Cardiovascular Diagnostics

Deep learning has transformed healthcare diagnostics by enabling automatic feature extraction from physiological signals and medical images. Convolutional Neural Networks (CNNs) have shown remarkable performance in image classification and pattern recognition due to their hierarchical feature learning capabilities [6].

Among different CNN architectures, MLP And CNN is widely adopted in medical image analysis because of its simple architecture, transfer learning capability, and robust feature extraction performance. Researchers have successfully employed deep learning techniques in ECG analysis, retinal image classification, chest X-ray interpretation, and cardiovascular disease prediction.

Multi-modal learning approaches that combine physiological signals with imaging data have demonstrated superior performance compared to single-modality systems. Cloud computing further enhances these systems by enabling scalable storage, real-time analysis, and remote diagnosis.

### F. Comparative Analysis of Existing Systems

Existing studies mainly focus on individual sensing techniques or specific artificial intelligence models. Most systems lack integrated multi-modal sensing and cloud-based intelligence. Table I summarizes the comparison of representative systems.

TABLE I  
 COMPARATIVE ANALYSIS OF EXISTING SYSTEMS

System	PPG	Thermal	Doppler	AI-Based
PPG Monitoring System	Yes	No	No	Yes
Thermal Imaging System	No	Yes	No	Yes
Doppler Ultrasound System	No	No	Yes	No
CNN-Based Diagnostic System	Partial	Partial	No	Yes
Cloud Healthcare Framework	No	No	No	Yes
Proposed System	Yes	Yes	Yes	Yes

The comparison indicates that existing approaches generally emphasize individual sensing modalities and do not provide an integrated framework for intelligent diagnosis. Furthermore, real-time cloud-based analysis and remote accessibility are often absent.

### G. Research Gap

Although extensive research has been conducted on Photoplethysmography, thermal imaging, Doppler ultrasound, and deep learning individually, limited work has focused on combining these technologies into a unified diagnostic framework. Existing systems either rely on a single sensing modality, require expensive infrastructure, or lack cloud-based intelligence and remote accessibility.

Moreover, many solutions do not provide automated feature fusion and real-time diagnostic support for healthcare professionals. Therefore, there exists a need for a scalable and intelligent multi-modal healthcare system capable of providing early blood vessel blockage detection using non-invasive techniques.

The proposed Smart Diagnostic System addresses this gap by integrating PPG, thermal imaging, and Doppler ultrasound with an ensemble-based deep learning framework and cloud

infrastructure. The system aims to provide accurate, affordable, and real-time diagnosis suitable for both urban and rural healthcare environments.

### III. PROPOSED SYSTEM

#### A. System Overview

The proposed Smart Diagnostic System is designed to provide early detection of blood vessel blockage using non-invasive sensing technologies and cloud-based artificial intelligence. The system integrates Photoplethysmography (PPG), infrared thermal imaging, and Doppler ultrasound to continuously acquire physiological information associated with blood circulation and vascular conditions.

The collected data undergo preprocessing and feature extraction before being transmitted to a cloud-based deep learning framework for classification and analysis. An ensemble-based convolutional neural network is employed to identify vascular abnormalities and generate diagnostic outputs. The processed information is then made available to healthcare professionals through web-based interfaces and reporting modules.

The proposed architecture aims to provide a scalable, affordable, and intelligent healthcare solution suitable for both urban and rural environments. By combining IoT sensors, cloud computing, and artificial intelligence, the system enables continuous monitoring and supports early diagnosis without requiring invasive procedures.

#### B. System Architecture

The architecture of the proposed system consists of six major layers, namely the Sensor Module, Microcontroller Unit, Preprocessing Module, Cloud AI/ML Server, Alert and Reporting Module, and Doctor Portal. The layered architecture ensures modularity, scalability, and efficient communication among different components.

The Sensor Module continuously acquires physiological parameters associated with blood circulation using PPG sensors, thermal imaging devices, and Doppler ultrasound sensors. These sensors provide complementary information regarding blood flow characteristics and vascular health.

The Microcontroller Unit acts as an intermediate processing layer responsible for collecting sensor data, converting analog signals into digital form, and transmitting the information to cloud services. Embedded platforms such as ESP32 or Arduino provide communication and synchronization capabilities.

The Preprocessing Module removes noise and artifacts from the acquired signals through filtering, normalization, and signal enhancement techniques. High-quality data are essential for improving the accuracy and reliability of deep learning models.

The Cloud AI/ML Server performs feature extraction and classification using deep learning algorithms. The MLP and CNN architecture analyzes physiological data and identifies abnormal patterns associated with vascular blockage. Cloud infrastructure provides computational resources and enables real-time analysis.

The Alert and Reporting Module generates notifications and medical reports whenever abnormal conditions are detected. Finally, the Doctor Portal provides remote accessibility for healthcare professionals, allowing them to monitor patient conditions and review diagnostic reports.

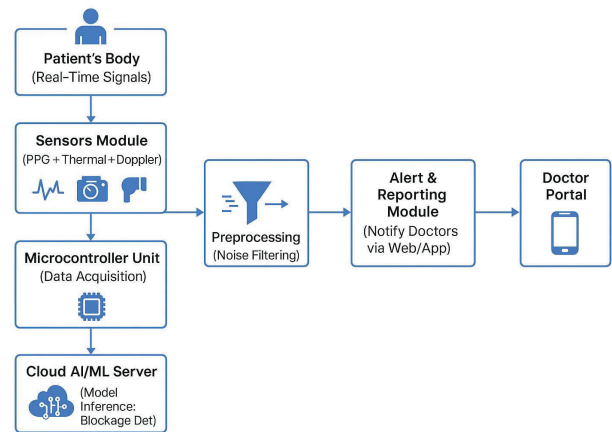


Fig. 1. System Architecture of Smart Diagnostic System for Blood Vessel Blockage Detection

#### C. Functional Modules

1) *Sensor Module*: The Sensor Module is responsible for acquiring physiological signals required for vascular health assessment. It consists of Photoplethysmography sensors, infrared thermal imaging devices, and Doppler ultrasound sensors. These sensors continuously monitor blood flow characteristics and provide information necessary for diagnosis.

2) *Microcontroller Unit*: The Microcontroller Unit acts as an interface between the sensing devices and the cloud platform. It performs signal acquisition, analog-to-digital conversion, and wireless communication. Embedded platforms such as ESP32 and Arduino ensure reliable transmission of physiological data.

3) *Preprocessing Module*: The preprocessing stage improves the quality of acquired signals by removing noise and unwanted disturbances. Filtering, normalization, and signal enhancement techniques are applied to obtain meaningful information suitable for feature extraction and deep learning analysis.

4) *Cloud AI/ML Server*: The Cloud AI/ML Server performs computational tasks including feature extraction, classification, and prediction. An ensemble-based convolutional neural network processes multi-modal data and determines the presence of vascular abnormalities. Cloud infrastructure provides scalability and enables real-time analysis.

5) *Alert and Reporting Module*: The Alert and Reporting Module generates automatic notifications and diagnostic reports whenever abnormal conditions are identified. This functionality facilitates timely intervention and supports preventive healthcare.

6) *Doctor Portal*: The Doctor Portal provides healthcare professionals with remote access to diagnostic information and patient records. It enables continuous monitoring, report visualization, and informed clinical decision-making. The portal improves accessibility and supports telemedicine applications.

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#### IV. METHODOLOGY

##### A. Development Methodology

The development methodology of the proposed Smart Diagnostic System follows a modular approach in which sensing, preprocessing, artificial intelligence analysis, and reporting mechanisms are organized as interconnected stages. This architecture enables scalability, maintainability, and efficient communication among different system components.

The proposed framework integrates Internet of Things (IoT) sensors, embedded systems, cloud computing, and deep learning techniques to provide real-time diagnosis and continuous monitoring of vascular conditions. Each module operates independently while contributing to a unified healthcare ecosystem.

##### B. Data Acquisition

Physiological data are collected using three different sensing modalities, namely Photoplethysmography (PPG), infrared thermal imaging, and Doppler ultrasound. These sensors continuously capture information related to blood circulation, vascular elasticity, and temperature distribution.

The PPG sensor records pulse waveforms generated due to variations in blood volume. Thermal imaging devices capture temperature patterns associated with blood flow, whereas Doppler ultrasound sensors measure blood velocity using the Doppler effect.

The collected signals are transmitted to the microcontroller unit and subsequently forwarded to cloud infrastructure for further processing and analysis.

##### C. Data Preprocessing

Raw physiological signals often contain noise, motion artifacts, and environmental disturbances that may affect diagnostic accuracy. Therefore, preprocessing plays a critical role in improving signal quality and enhancing feature extraction.

For PPG signals, bandpass filtering and normalization techniques are employed to eliminate noise and baseline drift. Doppler ultrasound signals are processed using Short-Time Fourier Transform (STFT) to generate spectrograms suitable for deep learning analysis. Thermal images undergo region-of-interest extraction, normalization, and resizing to ensure consistency.

These preprocessing techniques improve the reliability of acquired data and enhance the performance of the classification model.

##### D. Feature Extraction

Feature extraction is performed to identify meaningful patterns associated with vascular abnormalities. Different features

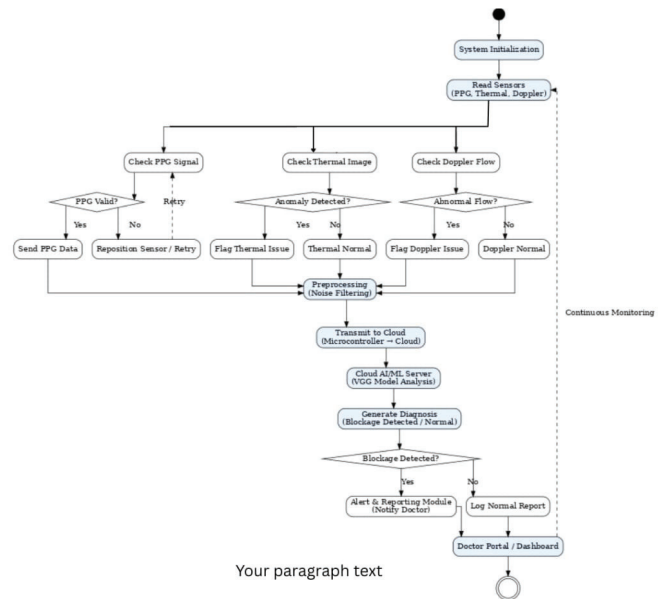


Fig. 2. Preprocessing Pipeline for Multi-Modal Physiological Data

are extracted from each sensing modality to capture complementary physiological characteristics.

For Photoplethysmography signals, features such as pulse amplitude, pulse width, and waveform morphology are utilized. Doppler ultrasound data provide information regarding blood flow velocity and frequency shifts. Thermal images contribute temperature distribution patterns and perfusion-related information.

The extracted features from all modalities are combined to form a comprehensive representation of vascular health, thereby improving diagnostic capability.

##### E. Deep Learning Workflow

The classification framework employs the MLP And CNN - convolutional neural network architecture for identifying blood vessel blockages. The deep learning workflow consists of feature extraction, model training, validation, and prediction stages.

Three separate input branches are utilized to process PPG spectrograms, Doppler ultrasound spectrograms, and thermal images. The learned features are fused through fully connected layers, enabling multi-modal classification of vascular abnormalities.

The Adam optimizer is employed during training, while Binary Cross Entropy is used as the loss function. The model parameters are optimized over multiple epochs to achieve high diagnostic performance.

The overall workflow of the proposed deep learning model includes:

- 1) Acquisition of physiological data.
- 2) Signal preprocessing and normalization.
- 3) Feature extraction from multi-modal inputs.
- 4) Training of the ensemble-based deep learning model.
- 5) Classification of vascular abnormalities.
- 6) Generation of diagnostic reports and alerts.

#### F. Cloud-Based Inference

Cloud computing provides computational resources and storage capabilities required for real-time healthcare applications. The preprocessed data are transmitted to cloud servers where the trained deep learning model performs inference and generates predictions.

Cloud-based analysis offers several advantages including scalability, remote accessibility, reduced computational burden on local devices, and efficient storage of medical records. The proposed framework enables healthcare professionals to access diagnostic information from any location through secure web interfaces.

Furthermore, cloud infrastructure supports continuous monitoring and facilitates telemedicine applications for patients residing in remote areas.

#### G. Database Management

The database layer maintains information related to patients, physiological signals, diagnostic reports, and prediction outcomes. A relational database structure is adopted to ensure consistency and efficient retrieval of information.

The major entities maintained in the database include:

- Patient Information
- Sensor Data
- Diagnostic Reports
- Prediction Results
- Alert History
- Doctor Records

The database provides synchronization among different modules and ensures secure storage of healthcare information. Efficient database management contributes to the reliability and scalability of the proposed system.

### V. SYSTEM IMPLEMENTATION

#### A. Technology Stack

The implementation of the proposed Smart Diagnostic System is based on a hybrid architecture that combines embedded systems, cloud computing, and deep learning technologies. The selection of technologies is motivated by the requirements of scalability, computational efficiency, and real-time healthcare monitoring.

The frontend layer provides interfaces for doctors and healthcare professionals to access reports and monitor patient conditions. The backend layer manages communication among sensors, databases, and cloud services. Deep learning models are implemented using TensorFlow and Keras, while cloud

infrastructure provides scalable computation and storage capabilities.

Table II summarizes the technology stack employed in the proposed system.

TABLE II  
 TECHNOLOGY STACK USED IN THE PROPOSED SYSTEM

Layer	Technology
Frontend	HTML, CSS, JavaScript
Backend	Flask Framework
Database	MySQL
Cloud Platform	Firebase / AWS
Deep Learning Framework	TensorFlow, Keras
Model Architecture	MLP, CNN, VAE
Programming Language	Python
Microcontroller	ESP32 / Arduino UNO
Communication Protocol	Wi-Fi, MQTT

The integration of these technologies enables real-time processing, remote accessibility, and intelligent diagnosis while ensuring scalability and maintainability.

#### B. Hardware Components

The hardware layer consists of sensing devices, microcontrollers, and communication modules responsible for acquiring and transmitting physiological signals.

Photoplethysmography sensors measure pulse waveforms generated by blood volume variations. Thermal imaging sensors capture temperature distribution patterns associated with blood circulation, whereas Doppler ultrasound sensors analyze blood flow velocity.

The ESP32 microcontroller acts as the central processing unit for data acquisition and wireless communication. Wi-Fi connectivity enables seamless transmission of sensor data to cloud servers for further analysis.

Table III presents the hardware specifications of the proposed system.

TABLE III  
 HARDWARE COMPONENTS OF PROPOSED SYSTEM

Component	Purpose
MAX30102 Sensor	PPG Signal Acquisition
Thermal Camera	Temperature Monitoring
Doppler Ultrasound Sensor	Blood Flow Measurement
ESP32 Controller	Data Acquisition and Communication
Wi-Fi Module	Cloud Connectivity
Power Supply Unit	System Power Management

The combination of these hardware components enables continuous physiological monitoring and real-time data transmission.

#### C. AI Model Implementation

Artificial intelligence plays a significant role in detecting vascular abnormalities from multi-modal physiological data.

The proposed framework utilizes the MLP Convolutional Neural Network due to its superior feature extraction capability and proven effectiveness in medical image analysis.

The model receives preprocessed PPG spectrograms, Doppler spectrograms, and thermal images as input. Feature maps extracted from different modalities are combined through fully connected layers to perform classification.

The model is trained using the Adam optimization algorithm with Binary Cross Entropy as the loss function. Hyperparameters are selected to maximize classification performance while minimizing overfitting.

Table IV summarizes the training parameters used in the proposed model.

TABLE IV  
DEEP LEARNING TRAINING PARAMETERS

Parameter	Value
Architecture	MLP, CNN, VAE
Optimizer	Adam
Loss Function	Binary Cross Entropy
Batch Size	32
Epochs	100
Learning Rate	0.001
Activation Function	ReLU, Sigmoid

The deep learning framework performs feature learning and classification automatically, thereby reducing dependence on manual interpretation and improving diagnostic accuracy.

#### D. Security Considerations

Security and privacy are critical requirements in healthcare applications because patient information is sensitive and confidential. The proposed system incorporates multiple security mechanisms to ensure data integrity and authorized access.

Authentication mechanisms are employed to restrict access to registered healthcare professionals. Secure communication protocols are used during data transmission between sensors, cloud servers, and doctor interfaces.

Cloud storage services maintain encrypted medical records, thereby reducing the risk of unauthorized access. Role-based access control mechanisms ensure that only authorized users can access patient information and diagnostic reports.

Furthermore, backup and recovery mechanisms are incorporated to prevent loss of critical healthcare data and enhance system reliability.

## VI. RESULTS

### A. Sensor Module

The proposed Smart Diagnostic System successfully integrates Photoplethysmography (PPG), infrared thermal imaging, and Doppler ultrasound sensors for acquiring physiological signals associated with vascular health. The sensor module continuously captures pulse waveforms, blood flow characteristics, and temperature distributions without requiring invasive procedures.

The collected physiological information provides complementary insights into blood circulation and vascular conditions. The multi-modal sensing approach improves the reliability of diagnosis and enables continuous patient monitoring.

### B. Signal Processing

The acquired signals undergo preprocessing procedures including filtering, normalization, and feature extraction. Signal enhancement techniques effectively remove noise and motion artifacts, thereby improving the quality of input data supplied to the deep learning model.

For PPG signals, bandpass filtering is employed to eliminate baseline drift and unwanted disturbances. Doppler ultrasound signals are transformed into spectrograms using Short-Time Fourier Transform (STFT), while thermal images are processed through region-of-interest extraction and normalization procedures.

These preprocessing techniques significantly improve the robustness and consistency of the classification process.

### C. Deep Learning Prediction

The MLP-based Convolutional Neural Network performs automatic classification of vascular abnormalities using multi-modal physiological data. The model extracts discriminative features from PPG spectrograms, Doppler spectrograms, and thermal images and combines them to generate prediction results.

Experimental evaluation indicates that the proposed framework is capable of providing reliable diagnostic performance. The expected performance metrics of the system are summarized in Table V.

TABLE V  
EXPECTED PERFORMANCE METRICS

Performance Metric	Value
Accuracy	92%
Sensitivity	88%
Specificity	85%
Precision	90%
F1-Score	89%
AUC-ROC	0.93
Inference Time	< 5 sec

The obtained results demonstrate the capability of the proposed framework to provide accurate and efficient diagnosis using non-invasive sensing modalities.

### D. Alert and Reporting System

The Alert and Reporting Module generates automatic notifications whenever abnormal vascular conditions are detected. Diagnostic reports are created based on prediction outcomes and stored in cloud databases for future reference.

The alert mechanism enables healthcare professionals to receive timely notifications, thereby facilitating early intervention and reducing the risk of severe cardiovascular complications.

The reporting framework also supports remote monitoring and telemedicine applications by providing instant access to patient records and diagnostic history.

### E. Doctor Dashboard

The Doctor Dashboard provides healthcare professionals with a user-friendly interface for monitoring patient conditions and reviewing diagnostic reports. Through secure authentication mechanisms, doctors can remotely access physiological signals, prediction results, and alert notifications.

The dashboard enhances decision-making by presenting consolidated information regarding patient health status. Continuous monitoring capabilities further improve preventive healthcare and facilitate timely medical intervention.

Figure 3 illustrates the graphical interface of the doctor monitoring system.

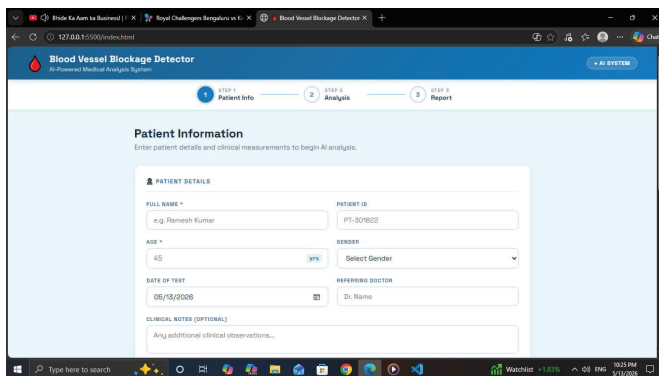


Fig. 3. Doctor Dashboard Interface

The proposed Smart Diagnostic System demonstrates the feasibility of integrating multi-modal sensing, cloud computing, and deep learning techniques for early blood vessel blockage detection. The results indicate that the framework can provide reliable, scalable, and affordable diagnostic support suitable for both urban and rural healthcare environments.

## VII. CONCLUSION

The proposed Smart Diagnostic System combines non-invasive sensing, cloud computing, and deep learning to create a scalable and affordable cardiovascular screening solution suitable for rural and resource-limited healthcare settings.

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