Recognizing Coronary Artery Disease (CAD) Using PPG Signals Through Deep Learning

A Project Work Submitted to Jawaharlal Nehru Technological University Kakinada, Kakinada in the Partial Fulfillment for the award of the degree of

Bachelor of Technology

in

Artificial Intelligence & Machine Learning

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Certificate

This is to certify that the project entitled **"Recognizing Coronary Artery Disease (CAD) Using PPG Signals Through Deep Learning"** is the bonafide work of

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DECLARATION

We **K. Venkata Rohith (RegdNo 22KQ1A6147)**, **G. Samuel (RegdNo 22KQ1A6142)**, **A. V. Tejaswani (RegdNo 22KQ1A6101)**, **E. Akhila (RegdNo 22KQ1A6106)**, and **Sk. Yasmeen (RegdNo 22KQ1A6125)** are hereby declare that the project report titled "**Recognizing Coronary Artery Disease (CAD) Using PPG Signals Through Deep Learning**" under the guidance of **Raghunath Reddy, M.Tech.,Ph.D** Associate Professor of **Artifical Intelligence and Machine Learning** is submitted in partial fulfillment of the require-ments for the award of the Degree of Bachelor of Technology in **Artifical Intelligence and Machine Learning**.

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Contents

Abstract

Coronary Artery Disease (CAD) is one of the leading causes of cardiovascular mortality worldwide. Early and reliable detection is essential to reduce severe complications and improve patient survival. Conventional diagnostic techniques such as angiography and stress testing are invasive, expensive, and unsuitable for large-scale or continuous monitoring. Therefore, there is a need for a non-invasive and intelligent screening solution.

This project presents a deep learning-based framework for CAD detection using Photoplethysmography (PPG) signals and clinical risk factors. PPG is a non-invasive optical signal that measures blood volume variations and is widely available in wearable health monitoring devices. Raw PPG signals are preprocessed through noise removal, normalization, and segmentation before being analyzed using a hybrid Convolutional Neural Network–Bidirectional Long Short-Term Memory (CNN–BiLSTM) architecture. The CNN layers extract local morphological features, while the BiLSTM layers capture temporal dependencies in the pulse waveform.

In addition to signal-based features, clinical attributes such as age, gender, diabetes status, cholesterol level, and obesity are integrated through feature fusion to enhance predictive performance. To improve diagnostic reliability, a patient-level Top-K hybrid aggregation strategy with optimized threshold selection using Youden's Index is employed.

The proposed system achieves a patient-level accuracy of 87.01%, sensitivity of 85.95%, specificity of 87.97%, and a ROC-AUC of 0.95. These results demonstrate strong class separability and clinically balanced performance. The framework provides an effective, non-invasive, and scalable solution for CAD screening and has potential for integration into wearable and real-time cardiovascular monitoring systems.

List of Abbreviations

Acronym	Abbreviation
1D	One Dimensional
2D	Two Dimensional
3D	Three Dimensional
CAD	Coronary Artery Disease
MIMIC	Medical Information Mart for Intensive Care
PPG	Photoplethysmography
DL	Deep Learning
ML	Machine Learning
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory
RNN	Recurrent Neural Network
ECG	Electrocardiogram
HRV	Heart Rate Variability
SNR	Signal-to-Noise Ratio
ReLU	Rectified Linear Unit
AUC	Area Under the Curve
ROC	Receiver Operating Characteristic
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative

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Chapter 1

Introduction

1.1 Background

Cardiovascular diseases are among the leading causes of death worldwide, and Coronary Artery Disease (CAD) is one of the most critical forms [1]. CAD occurs when coronary arteries become narrowed or blocked due to plaque accumulation, reducing blood flow to the heart muscle. Early detection is essential to prevent severe complications such as myocardial infarction and heart failure.

Conventional diagnostic methods such as coronary angiography, stress testing, and electrocardiography (ECG) are often expensive, require hospital infrastructure, and may involve invasive procedures [2]. These limitations highlight the need for non-invasive, low-cost, and automated screening systems.

Photoplethysmography (PPG) is a simple and non-invasive optical technique that measures blood volume variations in peripheral vessels [3, 4]. PPG sensors are widely integrated into wearable devices such as smartwatches and fitness bands. Since CAD affects vascular elasticity and blood flow dynamics, it indirectly alters PPG waveform morphology, making it a promising signal for non-invasive CAD detection.PPG signals have been widely studied for cardiovascular health assessment [5].

1.2 Motivation

Recent advancements in deep learning have enabled automatic feature extraction from physiological signals [6]. Traditional machine learning methods rely on handcrafted features, which may fail to capture complex temporal and morphological variations.Recent advances in deep learning have enabled automatic feature extraction from physiological signals without relying on handcrafted features [7]. Deep learning-based PPG

classification models have demonstrated promising performance in cardiovascular diagnosis [6, 8]. Hybrid CNN-LSTM architectures further enhance temporal modeling capability [9]. In contrast, deep learning models such as Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks can learn discriminative representations directly from raw signals [7].

In addition to waveform characteristics, clinical risk factors such as age, gender, diabetes status, cholesterol levels, and obesity significantly influence CAD risk. Integrating signal-based and clinical features can improve prediction robustness and clinical relevance.

Furthermore, segment-level predictions may lead to inconsistent decisions due to signal variability. Therefore, patient-level aggregation strategies with optimized threshold selection are essential to ensure reliable and clinically meaningful diagnosis.

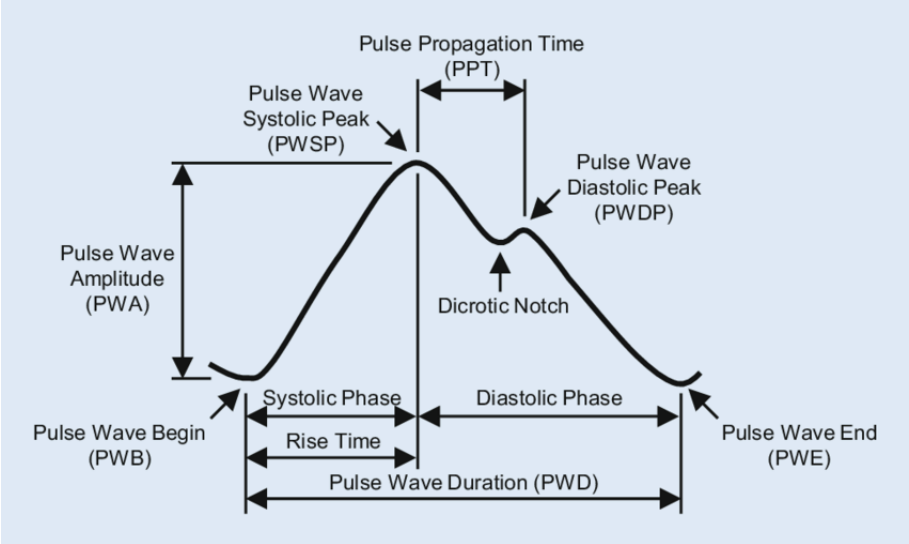

Figure 1.1: Typical Photoplethysmography (PPG) waveform showing systolic peak, dicrotic notch, and diastolic phase.

The PPG waveform consists of a systolic peak corresponding to ventricular contraction and a dicrotic notch representing aortic valve closure. These morphological characteristics provide important cardiovascular information and can be used for detecting abnormalities related to Coronary Artery Disease.

1.3 Problem Statement

The problem addressed in this project is the automatic detection of Coronary Artery Disease using PPG signals and associated clinical risk factors. Given raw PPG recordings collected from subjects, the system must preprocess the signals, extract meaningful representations, and classify individuals into CAD and non-CAD categories.

The main challenges include:

- Handling noisy and artifact-prone PPG signals
- Capturing both morphological and temporal characteristics
- Integrating clinical risk factors with signal features
- Achieving high sensitivity for screening applications
- Producing reliable patient-level predictions

To address these challenges, a hybrid CNN–BiLSTM framework with feature fusion and patient-level aggregation is proposed.

1.4 Objectives

The primary objectives of this project are:

- To develop a non-invasive CAD detection framework using PPG signals.
- To integrate clinical risk factors with learned signal representations.
- To implement signal preprocessing including filtering, normalization, and segmentation.
- To design a hybrid CNN–BiLSTM architecture for automatic feature learning.
- To implement patient-level Top-K aggregation with optimized threshold selection.
- To evaluate performance using accuracy, sensitivity, specificity, precision, F1-score, and ROC-AUC.

1.5 Scope of the Project

This project focuses on binary classification of CAD and healthy subjects using PPG signals combined with clinical risk factors obtained from publicly available datasets. The proposed system is intended for screening applications and can be extended for real-time deployment in wearable or remote monitoring systems.

The framework is designed to be scalable and adaptable for future improvements, including multi-class cardiovascular risk prediction and real-time implementation.

1.6 Organization of the Report

This report is structured to systematically present the development and evaluation of the proposed Coronary Artery Disease (CAD) detection framework.

Chapter 1 (Introduction) presents the background of CAD, motivation for non-invasive detection, problem statement, and objectives of the proposed system.

Chapter 2 (Literature Review) surveys existing research on CAD detection using physiological signals, machine learning, and deep learning approaches, and identifies research gaps addressed in this work.

Chapter 3 (Theoretical Background) explains the fundamental concepts of cardiovascular physiology, CAD pathology, Photoplethysmography (PPG), signal processing techniques, and deep learning principles relevant to the proposed framework.

Chapter 4 (Dataset Description) describes the dataset source, structure, preprocessing pipeline, segmentation strategy, labeling methodology, and clinical feature integration.

Chapter 5 (Methodology) details the proposed hybrid CNN–BiLSTM model, multimodal feature fusion strategy, loss function design, and patient-level aggregation mechanism.

Chapter 6 (System Architecture and Design) presents the overall system workflow, architectural components, modular design principles, and scalability considerations.

Chapter 7 (Implementation and Training) explains the system environment, model implementation details, hyperparameter configuration, and training strategy.

Chapter 8 (Experimental Setup and Protocol) describes the evaluation protocol, patient-level splitting strategy, performance metrics, and reproducibility measures.

Chapter 9 (Results and Discussions) presents experimental results, performance analysis, comparison with existing methods, and interpretation of findings.

Chapter 10 (Conclusion) summarizes the major contributions of the study and outlines future research directions for enhancing clinical applicability and system scalability.

Chapter 2

Literature Review

2.1 Introduction

Coronary Artery Disease (CAD) remains one of the leading causes of mortality worldwide. Early detection and continuous monitoring are critical to reducing cardiac-related deaths. Conventional diagnostic techniques such as coronary angiography, electrocardiography (ECG), and stress testing are clinically reliable; however, these methods are invasive, expensive, and unsuitable for continuous or large-scale screening applications.

Recent advancements in signal processing and deep learning have enabled the use of non-invasive physiological signals such as Photoplethysmography (PPG) for cardiovascular disease detection. This chapter reviews existing research on CAD detection using traditional clinical methods, PPG-based analysis, conventional machine learning models, modern deep learning architectures, and patient-level evaluation strategies.

2.2 Traditional CAD Detection Methods

Conventional CAD diagnosis relies on imaging and ECG-based analysis [2]. While effective, these approaches are invasive and unsuitable for large-scale screening.

Historically, CAD diagnosis has relied on clinical imaging and electrophysiological techniques including:

- Coronary Angiography
- Electrocardiography (ECG)
- Echocardiography
- Stress Testing

- Cardiac CT Imaging

Although these approaches provide accurate diagnosis, they present several limitations:

- Invasive procedures (e.g., angiography)
- High operational cost
- Requirement of specialized hospital infrastructure
- Unsuitability for long-term or remote monitoring

These limitations have motivated researchers to explore non-invasive and automated alternatives using wearable-compatible signals.

2.3 Photoplethysmography in Cardiovascular Analysis

Photoplethysmography (PPG) is a low-cost, non-invasive optical technique that measures variations in blood volume within peripheral circulation [3]. PPG waveform morphology reflects cardiovascular dynamics, and several waveform-derived parameters such as Pulse Wave Velocity (PWV), Reflection Index (RI), Stiffness Index (SI), and Augmentation Index (AI) are associated with arterial stiffness and CAD progression.

Banerjee et al. (2021) [8] demonstrated that PPG-based features can effectively distinguish CAD patients from healthy subjects using CNN-based architectures.

Some recent studies have transformed PPG signals into time–frequency representations such as spectrograms or scalograms before applying deep learning models, which increases computational complexity and memory requirements [9, 10].

2.4 Early Machine Learning-Based Approaches

Initial CAD detection systems relied on traditional Machine Learning classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Random Forest, Decision Trees, and Logistic Regression.

The typical pipeline included signal preprocessing, manual feature extraction, feature selection, and classification.Wearable PPG-based CAD detection systems have gained significant attention [11, 12]. Multimodal integration of PPG with clinical risk factors further enhances diagnostic performance [13]. Although these approaches achieved moderate performance (80–85%), they were heavily dependent on handcrafted features and lacked robustness to signal variability and noise.

These limitations encouraged the adoption of deep learning-based frameworks.

2.5 Deep Learning in Biomedical Signal Classification

Deep learning models automatically learn hierarchical representations directly from raw signals, reducing dependence on manual feature engineering.Deep learning models have significantly improved physiological signal classification. Liang et al. demonstrated CNN-LSTM models for PPG-based cardiovascular diagnosis [6]. Banerjee et al. applied CNN architectures for CAD detection using PPG signals [8]. Shan et al. further validated CNN-based PPG classification [14].

2.5.1 Convolutional Neural Networks (CNN)

CNNs are effective in extracting local morphological features from waveform data. In PPG analysis, CNN layers learn discriminative patterns such as peak shapes, slope variations, and waveform distortions.

2.5.2 Recurrent Neural Networks and LSTM

Physiological signals are time-series in nature. Long Short-Term Memory (LSTM) networks capture temporal dependencies and mitigate vanishing gradient problems. Liang et al. (2020) proposed CNN-LSTM architectures for PPG-based cardiovascular classification and achieved improved performance [6].

2.5.3 Hybrid CNN-BiLSTM Architectures

Hybrid architectures combine CNN for spatial feature extraction and Bidirectional LSTM (BiLSTM) for enhanced temporal modeling.Hybrid CNN-LSTM architectures have shown improved temporal modeling [9]. Recent works introduced attention-enhanced models [15] and transformer-based architectures [10] for improved classification robustness. BiLSTM processes sequence information in both forward and backward directions, improving representation capability. Recent studies indicate that hybrid models outperform standalone CNN or traditional ML classifiers.

2.6 Comparative Analysis of Existing Methods

Table 2.1: Comparative Analysis of CAD Detection Methods Using PPG Signals

Study	**Method**	**Accuracy**
Banerjee et al. (2021)	CNN	88%
Liang et al. (2020)	CNN-LSTM	91%
Early ML Approaches	SVM / KNN	80–85%
Proposed Work	CNN-BiLSTM + Top-K Aggregation	87.01%

2.7 Research Gaps Identified

Despite significant progress, several limitations remain in existing studies:

- Limited use of Bidirectional LSTM for enhanced temporal modeling.
- Evaluation performed at segment level rather than patient level, leading to inflated performance estimates.
- Inadequate patient-level aggregation strategies for robust diagnosis.
- Limited integration of clinical risk factors with deep learning-based PPG models.
- Limited evaluation on large-scale real-world clinical datasets.
- Need for computationally efficient yet clinically reliable architectures.

2.8 Motivation for Proposed Work

Based on the identified gaps, the proposed study adopts a hybrid CNN-BiLSTM deep learning framework integrated with clinical risk factors for CAD detection using PPG signals.

The system incorporates:

- CNN layers for spatial feature extraction.
- BiLSTM layers for bidirectional temporal modeling.
- Fusion of clinical attributes with learned signal features.
- Patient-level Top-K aggregation strategy.
- ROC-based threshold optimization using Youden's Index.

The objective is to develop a reliable, scalable, and clinically meaningful non-invasive CAD screening system suitable for wearable health monitoring environments.

2.9 Summary

This chapter reviewed traditional CAD diagnostic techniques, PPG-based cardiovascular analysis, conventional machine learning models, and deep learning-based approaches. The literature indicates that hybrid deep learning architectures combined with patient-level evaluation strategies provide more realistic and clinically meaningful performance. Motivated by these findings, the proposed work focuses on a CNN-BiLSTM framework with clinical feature fusion and patient-level aggregation for robust CAD detection.

Chapter 3

Theoretical Background

3.1 Introduction

This chapter presents the theoretical foundations required to understand the proposed Coronary Artery Disease (CAD) detection framework. It covers cardiovascular physiology, CAD pathology, Photoplethysmography (PPG) principles, signal preprocessing concepts, and deep learning fundamentals. These concepts form the scientific basis of the proposed CNN–BiLSTM based CAD detection system.

Understanding the physiological and mathematical principles behind cardiovascular signal analysis is essential for designing reliable non-invasive diagnostic systems. The integration of biomedical signal processing with artificial intelligence requires a multidisciplinary foundation combining cardiology, optics, signal theory, and computational modeling.

3.2 Overview of the Cardiovascular System

The cardiovascular system is responsible for circulating oxygenated blood throughout the body. It consists of the heart and a network of blood vessels including arteries, veins, and capillaries. The heart functions as a muscular pump that maintains systemic and pulmonary circulation.

Efficient blood circulation ensures oxygen delivery, nutrient transport, metabolic waste removal, and hormonal regulation. Any impairment in coronary circulation can significantly impact myocardial function and overall systemic health.

3.2.1 Structure of the Heart

The human heart consists of four chambers:

- Left Atrium
- Right Atrium
- Left Ventricle
- Right Ventricle

The left ventricle pumps oxygenated blood into systemic circulation through the aorta, while the right ventricle pumps deoxygenated blood to the lungs for oxygenation.

The coordinated contraction of these chambers follows the cardiac cycle, which consists of systole (contraction phase) and diastole (relaxation phase). Electrical impulses originating from the sinoatrial (SA) node regulate rhythmic contraction, maintaining consistent hemodynamic flow.

3.2.2 Coronary Arteries

Coronary arteries supply oxygen-rich blood to the heart muscle. The two primary coronary arteries are:

- Left Coronary Artery (LCA)
- Right Coronary Artery (RCA)

The Left Coronary Artery further divides into the Left Anterior Descending (LAD) and Left Circumflex (LCX) arteries. Blockage in these arteries leads to Coronary Artery Disease.

Adequate coronary perfusion is critical because myocardial cells have high oxygen demand. Even partial obstruction can impair cardiac function and alter systemic circulation patterns.

3.3 Coronary Artery Disease (CAD)

Coronary Artery Disease occurs due to the accumulation of atherosclerotic plaque within coronary arteries. This narrowing reduces myocardial blood supply, potentially leading to angina, myocardial infarction, or cardiac arrest.

CAD is one of the leading causes of global mortality. Early detection is essential to prevent severe cardiovascular events.

3.3.1 Pathophysiology of CAD

The progression of CAD involves:

1. Endothelial dysfunction
2. Lipid deposition
3. Plaque formation
4. Arterial narrowing
5. Reduced myocardial perfusion

As plaque accumulates, arterial elasticity decreases and vascular stiffness increases. These structural changes alter pulse wave velocity and peripheral hemodynamic behavior.

Arterial stiffness and altered hemodynamics caused by CAD influence peripheral pulse propagation. These changes indirectly affect PPG waveform morphology, making PPG a potential non-invasive marker for CAD detection.

Reduced compliance modifies systolic peak amplitude, dicrotic notch timing, and waveform slope characteristics. These subtle morphological variations can be learned by deep neural networks.

3.4 Photoplethysmography (PPG)

Photoplethysmography is a non-invasive optical technique used to measure blood volume changes in peripheral circulation. It operates by emitting light into the skin and measuring the reflected or transmitted light intensity. PPG operates based on the Beer-Lambert law and measures pulsatile blood volume variations [3]. The waveform consists of AC and DC components that reflect cardiovascular activity [4].

PPG sensors are widely used in wearable devices such as smartwatches and pulse oximeters due to their low cost, simplicity, and portability.

3.4.1 Working Principle

PPG is based on the Beer-Lambert Law:

$$I = I_0 e^{-\alpha c l}$$

where I_0 is incident light intensity, I is detected light intensity, α is absorption coefficient, c is blood concentration, and l is optical path length.

Variations in blood volume during the cardiac cycle alter light absorption, producing a pulsatile waveform. The pulsatile component corresponds to arterial blood flow synchronized with heartbeats.

3.4.2 Components of PPG Signal

PPG consists of two main components:

- DC Component – Represents baseline tissue and non-pulsatile blood absorption.
- AC Component – Represents pulsatile blood flow due to cardiac activity.

The AC component is primarily analyzed for cardiovascular assessment because it reflects dynamic blood volume changes associated with cardiac cycles.

3.4.3 PPG Waveform Morphology

A typical PPG waveform includes:

- Systolic Peak
- Dicrotic Notch
- Diastolic Wave

The systolic peak corresponds to ventricular contraction, while the dicrotic notch indicates aortic valve closure. The diastolic wave reflects peripheral vascular resistance.

Changes in peak amplitude, slope, reflection index, and timing characteristics may indicate vascular stiffness and hemodynamic alterations associated with CAD.

3.5 Signal Processing Fundamentals

PPG signals are susceptible to noise from motion artifacts, respiration, and ambient light. Signal processing techniques are required before classification. PPG signals are sensitive to motion artifacts and environmental noise [16]. Bandpass filtering and normalization improve signal stability.

Proper preprocessing enhances signal quality and reduces variability across patients.

3.5.1 Filtering

A Butterworth bandpass filter is commonly applied to remove baseline drift and high-frequency noise. The magnitude response is:

$$|H(j\omega)|^2 = \frac{1}{1 + \left(\frac{\omega}{\omega_c}\right)^{2n}}$$

where ω_c is the cutoff frequency and n is filter order.

Butterworth filters are preferred due to their maximally flat frequency response in the passband. In the proposed framework, filtering is followed by normalization and signal segmentation before inputting the data into the deep learning model.

3.6 Deep Learning Fundamentals

Deep learning models learn hierarchical representations directly from raw signals without manual feature extraction. Convolutional Neural Networks (CNN) are effective in extracting local morphological features from 1D biomedical signals [7]. Long Short-Term Memory (LSTM) networks capture temporal dependencies, making them suitable for time-series data [6]. Recent models incorporate attention mechanisms for improved feature weighting [15].

The combination of CNN and LSTM provides complementary strengths: spatial feature extraction and temporal sequence modeling.

3.6.1 Artificial Neural Network (ANN)

A neuron computes:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

where:

- w_i = weights
- x_i = inputs
- b = bias
- f = activation function

Activation functions such as ReLU and Sigmoid introduce non-linearity, enabling complex pattern learning.

3.6.2 Convolutional Neural Networks (CNN)

CNN performs convolution to extract local patterns:

$$(S * K)(t) = \sum_{i} S(t-i)K(i)$$

CNN layers capture morphological characteristics such as peak structure, slope variations, and waveform distortions in PPG signals. Weight sharing reduces parameter count and improves generalization.

3.6.3 Long Short-Term Memory (LSTM)

LSTM networks capture long-term temporal dependencies in sequential PPG data.

The LSTM cell equations are:

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tanh(W_c x_t + U_c h_{t-1})$$

$$h_t = o_t \cdot \tanh(C_t)$$

These gating mechanisms regulate memory flow and prevent vanishing gradient problems, enabling stable learning across long sequences.

3.6.4 Bidirectional LSTM

Bidirectional LSTM processes sequence information in both forward and backward directions, enabling comprehensive temporal context modeling. This improves discrimination between CAD and non-CAD patterns by considering complete waveform dynamics.

3.7 Loss Functions and Optimization

To handle class imbalance in CAD detection, Focal Loss is used:

$$FL(p_t) = -\alpha(1 - p_t)^{\gamma} \log(p_t)$$

where α controls class weighting and γ reduces the impact of well-classified samples.

Optimization is performed using the Adam optimizer, which combines adaptive learning rates with momentum to improve convergence stability and reduce oscillations during gradient descent.

3.8 Evaluation Metrics

Performance is measured using:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

$$Sensitivity(Recall) = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$F1 = 2 \cdot \frac{Precision \cdot Sensitivity}{Precision + Sensitivity}$$

The Receiver Operating Characteristic (ROC) curve evaluates the trade-off between Sensitivity (True Positive Rate) and False Positive Rate across different thresholds.

$$TPR = \frac{TP}{TP + FN}$$

$$FPR = \frac{FP}{FP + TN}$$

The Area Under the ROC Curve (AUC) quantifies the overall discriminative ability of the model. An AUC value closer to 1 indicates better classification performance.

For CAD screening systems, higher sensitivity is prioritized to minimize the risk of missed positive cases, as false negatives can lead to severe clinical consequences.

3.9 Summary

This chapter presented the theoretical background necessary for CAD detection using PPG signals and deep learning. It covered cardiovascular physiology, CAD pathology, PPG principles, preprocessing fundamentals, CNN and BiLSTM architectures, optimization strategies, and evaluation metrics. These theoretical foundations support the development and validation of the proposed hybrid CNN–BiLSTM framework for non-invasive CAD classification.

Chapter 4

Dataset Description

4.1 Introduction

The performance of a deep learning model strongly depends on the quality, diversity, and structure of the dataset used for training and evaluation. In this project, Photoplethysmography (PPG) signals combined with clinical risk factors are utilized to detect Coronary Artery Disease (CAD). This chapter describes the dataset source, structure, labeling methodology, preprocessing pipeline, and preparation steps applied to generate high-quality input for the proposed CNN–BiLSTM framework.

Proper preprocessing and patient-level data organization are essential to ensure model reliability, prevent data leakage, and achieve clinically meaningful evaluation. In medical AI systems, even minor data inconsistencies can significantly influence predictive performance; therefore, careful dataset curation is critical.

The dataset consists of PPG signals collected from publicly available biomedical repositories. PPG-based cardiovascular datasets have been widely used in prior studies [6, 8]. Signal preprocessing includes filtering, normalization, and segmentation to ensure stable deep learning input representation [4].

4.2 Dataset Source

The dataset used in this study is derived from the MIMIC-III Waveform Database available through PhysioNet. This database contains real-world clinical physiological recordings collected from intensive care unit (ICU) patients.

MIMIC-III is widely recognized in biomedical research for its comprehensive collection of synchronized waveform signals and structured clin-

ical metadata. The use of real clinical recordings ensures variability in signal quality, patient demographics, and disease conditions, thereby enhancing model generalization.

The dataset includes:

- Raw PPG waveform recordings
- Patient-level identifiers
- CAD diagnostic labels
- Clinical attributes such as age, gender, diabetes status, cholesterol level, and obesity indicators

The inclusion of both physiological signals and clinical risk factors enables multimodal learning and improves the robustness of CAD classification. Multimodal datasets better reflect real-world diagnostic settings where waveform signals are interpreted alongside patient history.

4.3 Dataset Structure

Each PPG record is a continuous time-series signal sampled at 125 Hz. The waveform represents pulsatile blood volume changes corresponding to cardiac activity. Multiple recordings per patient allow the model to learn intra-patient variations (within same subject) and inter-patient variability (across subjects).

Time-series representation preserves temporal dependencies critical for modeling vascular compliance and pulse wave propagation characteristics. Since CAD affects arterial stiffness and hemodynamic response, subtle waveform distortions become discriminative features.

The processed dataset consists of segmented windows extracted from raw signals. Each segment is associated with:

- A binary CAD label (0 = Non-CAD, 1 = CAD)
- Corresponding clinical attributes
- Patient identifier (for aggregation and splitting)

Table 4.1: Summary of Dataset Characteristics

Signal Type	Photoplethysmography (PPG)
Sampling Frequency	125 Hz
Segment Length	50 samples (0.4 seconds)
Max Segments per Patient	300
Classes	CAD / Non-CAD
Clinical Features	Age, Gender, Diabetes, Cholesterol, Obesity
Data Format	CSV
Split Strategy	Patient-level Train-Test Split

The structured dataset ensures compatibility with deep learning frameworks while maintaining traceability to original patient identifiers for aggregation and evaluation.

4.4 Data Cleaning

Raw PPG signals often contain distortions due to:

- Motion artifacts
- Sensor displacement
- Baseline drift
- Respiration interference
- Ambient light variations

To improve signal quality, the following preprocessing steps are applied:

- Removal of corrupted and incomplete signal portions.
- Bandpass filtering to suppress low-frequency baseline drift and high-frequency noise.
- Smoothing to stabilize waveform morphology.

These operations enhance the signal-to-noise ratio while preserving diagnostically relevant features. Care was taken to ensure that filtering does not distort systolic peak timing or remove physiologically meaningful high-frequency components.

4.5 Signal Normalization

Amplitude variations occur across patients due to physiological and sensor differences. Min-Max normalization is applied to ensure consistent scaling:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

This transformation scales signal values between 0 and 1, preventing amplitude dominance and improving gradient stability during training. Normalization also reduces inter-device variability and improves model convergence speed.

4.6 Segmentation of PPG Signals

Continuous PPG recordings are divided into fixed-length windows of 50 samples (approximately 0.4 seconds at 125 Hz). Each window represents a training sample.

To prevent bias from patients with longer recordings, a maximum of 300 valid segments per patient is selected. Overlapping segmentation is applied to ensure adequate capture of waveform morphology even if a single segment does not contain a complete cardiac cycle.

Segmentation provides:

- Increased training samples
- Enhanced learning of local temporal features
- Reduced computational complexity

Window-based segmentation transforms long sequential data into structured mini-batch inputs suitable for parallelized deep learning training.

4.7 Clinical Feature Integration

In addition to PPG waveform data, the dataset includes patient-level clinical attributes:

- Age
- Gender
- Diabetes status
- Cholesterol level
- Obesity indicator

These features are normalized and processed through a dedicated dense network branch. The learned clinical representation is fused with signal-based features to improve classification performance.

Clinical variables provide complementary risk information that may not be directly observable in peripheral pulse waveforms. Multimodal fusion enhances predictive robustness by integrating structural and physiological indicators.

4.8 Labeling Strategy

Each segmented window inherits the CAD diagnosis of its corresponding patient. This ensures that all segments from a CAD patient are labeled as CAD and vice versa.

This patient-consistent labeling is critical for later patient-level aggregation and evaluation. Maintaining consistent labeling prevents misalignment between segment-level predictions and final patient-level classification.

4.9 Handling Class Imbalance

Medical datasets frequently exhibit class imbalance. CAD-positive cases may be underrepresented relative to healthy controls. To mitigate this issue, Focal Loss is employed during training. This loss function reduces the impact of easily classified samples and emphasizes harder examples, thereby improving sensitivity toward CAD cases.

Additionally, careful patient-level splitting ensures that imbalance does not disproportionately affect a single dataset partition.

4.10 Train-Test Split

A strict patient-level splitting strategy is adopted. All segments from a given patient are assigned exclusively to either the training or testing set. This prevents data leakage and ensures realistic performance evaluation.

Patient-level separation is critical because segment-level random splitting could artificially inflate performance by allowing the model to see data from the same patient in both training and testing sets.

4.11 Data Preparation for Deep Learning

Segmented PPG windows are reshaped into tensors suitable for CNN–BiLSTM input. Clinical attributes are processed in parallel and fused at the feature level.

Mini-batch training, data shuffling, and early stopping are applied to improve convergence and reduce overfitting. Data tensors are formatted to match input dimensions required by 1D convolutional layers and recurrent modules.

Efficient memory management and batch-based loading enable scalable training even with large waveform datasets.

4.12 Summary

This chapter detailed the dataset source, structure, preprocessing pipeline, segmentation strategy, clinical feature integration, and data preparation steps. By combining waveform analysis with patient-level clinical information and strict splitting protocols, the dataset preparation ensures reliable, unbiased, and clinically meaningful CAD detection performance suitable for real-world deployment.

Chapter 5

Methodology

5.1 Introduction

This chapter presents the complete methodological framework for detecting Coronary Artery Disease (CAD) using Photoplethysmography (PPG) signals combined with clinical risk factors. The proposed system adopts an end-to-end hybrid Convolutional Neural Network–Bidirectional Long Short-Term Memory (CNN–BiLSTM) architecture to automatically learn hierarchical representations from normalized PPG segments. The framework eliminates manual feature engineering and enables robust patient-level CAD prediction through multimodal learning and aggregation strategies.

Unlike conventional machine learning approaches that rely on handcrafted waveform features, the proposed methodology leverages deep hierarchical representation learning to capture both morphological and temporal patterns directly from raw physiological signals. This approach improves adaptability, reduces domain bias, and enhances generalization across diverse patient populations.

5.2 Signal Preprocessing and Segmentation

Raw PPG signals sampled at 125 Hz are first processed using a bandpass filter to remove baseline drift and high-frequency noise. Corrupted or flat-line segments are discarded to prevent misleading gradient updates during training. In addition to filtering, outlier detection is performed to eliminate abnormal amplitude spikes caused by motion artifacts or poor sensor contact.

Preprocessing ensures that the network receives physiologically meaningful waveform patterns while minimizing artifacts that could distort gradient optimization. Signal conditioning improves signal-to-noise ratio

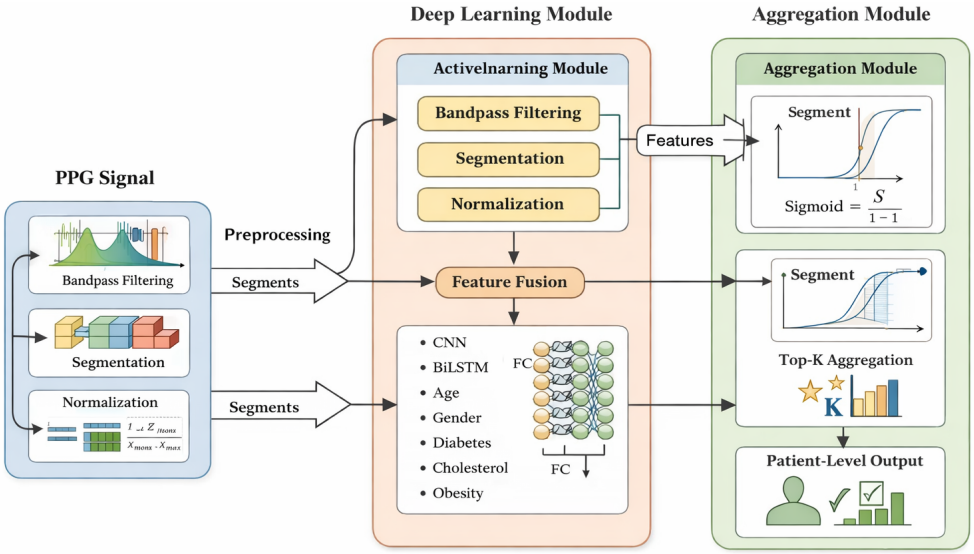

Figure 1: Proposed Coronary Artery Disease (CAD) detection architecture based on a hybrid CNN–BiLSTM model with clinical feature fusion and patient-level aggregation.

Figure 5.1: Proposed hybrid CNN–BiLSTM architecture with clinical feature fusion and Top-K patient-level aggregation.

(SNR) and enhances feature discriminability.

Min-Max normalization is applied to ensure numerical stability and consistent scaling across patients:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Normalization prevents gradient explosion and ensures that learning focuses on relative waveform morphology rather than amplitude magnitude variations due to sensor placement differences.

Continuous signals are segmented into fixed-length overlapping windows of 50 samples (0.4 seconds). Overlapping windows preserve waveform continuity and improve representation learning by capturing transitional cardiovascular dynamics. To prevent dominance of patients with longer recordings, a maximum of 300 valid segments per patient is retained.

This segmentation strategy converts long physiological recordings into structured mini-batch learning samples while preserving temporal coherence.

Each segment is represented as:

$$S_i \in \mathbb{R}^{50\times 1}$$

where 50 denotes time steps and 1 denotes the signal channel.

5.3 Hybrid CNN–BiLSTM Feature Learning

The convolutional operation used in spatial feature extraction is defined as:

$$y(t) = \sum_{k=0}^{K-1} x(t-k)w(k)$$

The CNN component consists of multiple convolutional layers with progressively increasing filter depths to learn hierarchical waveform representations. Initial layers focus on detecting basic morphological features such as edges and slopes, while deeper layers capture complex pulse shape variations associated with arterial stiffness, vascular irregularities, and microcirculatory abnormalities.

Batch normalization stabilizes internal covariate shifts, accelerates convergence, and improves gradient propagation across deep layers. MaxPooling reduces dimensionality, enhances translation invariance, and decreases computational complexity.

Following spatial feature extraction, the sequential representation is passed to a Bidirectional LSTM (BiLSTM) network:

$$h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}]$$

The forward and backward passes allow the model to learn temporal dependencies from both past and future contexts within each segment. This bidirectional modeling improves detection of subtle CAD-related abnormalities that may not be evident in isolated waveform regions.

The hybrid integration of CNN and BiLSTM enables simultaneous modeling of spatial morphology and temporal dynamics, offering superior representation learning compared to standalone CNN or LSTM architectures.

5.4 Clinical Feature Processing and Multimodal Fusion

Clinical attributes including age, gender, diabetes status, cholesterol level, and obesity indicators are normalized and processed through fully connected layers to learn nonlinear interactions between risk factors.

Let the clinical feature vector be:

$$C \in \mathbb{R}^d$$

where d represents the number of clinical features.

Feature fusion is implemented at the latent representation level. The signal-based representation F_s and clinical representation F_c are concatenated:

$$F_{fusion} = [F_s; F_c]$$

This multimodal strategy enhances discriminative capability by combining physiological waveform abnormalities with traditional cardiovascular risk indicators. Multimodal fusion improves robustness by leveraging complementary information sources, reducing reliance on a single modality.

5.5 Classification and Training Strategy

The final classification layer applies sigmoid activation:

$$P(CAD) = \frac{1}{1 + e^{-z}}$$

The sigmoid function transforms the output into a probability score between 0 and 1, enabling threshold-based decision making.

To address class imbalance, Focal Loss is employed:

$$FL(p_t) = -\alpha(1 - p_t)^{\gamma} \log(p_t)$$

where α balances class contributions and γ emphasizes difficult examples.

Model parameters are optimized using the Adam algorithm:

$$\theta_{t+1} = \theta_t - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

Adam combines adaptive learning rates with momentum-based updates, ensuring stable convergence even under non-convex optimization landscapes.

Regularization strategies including dropout, early stopping, validation monitoring, and mini-batch training are applied to prevent overfitting and ensure stable convergence. These mechanisms enhance generalization and reduce model variance.

5.6 Patient-Level Top-K Aggregation

Segment-level predictions may vary due to noise and physiological variability. Therefore, patient-level aggregation is performed.

For a patient with segment probabilities $\{P_1, P_2, ..., P_n\}$, the Top-K highest abnormal scores are selected:

$$Score = 0.7 \times Mean(TopK) + 0.3 \times Max(P_i)$$

This hybrid weighting strategy prioritizes highly abnormal segments while maintaining prediction stability through averaging.

Threshold optimization uses Youden's Index:

$$J = Sensitivity + Specificity - 1$$

The threshold maximizing J is selected to balance sensitivity and specificity. This aggregation mechanism mimics clinical practice, where physicians focus on the most abnormal waveform regions rather than averaging across entire recordings.

5.7 Summary

The proposed methodology integrates signal preprocessing, hierarchical CNN–BiLSTM feature learning, multimodal clinical fusion, Focal Loss optimization, and patient-level Top-K aggregation. The end-to-end framework enables automated, robust, and clinically meaningful CAD prediction without reliance on handcrafted features, while maintaining computational efficiency and deployment feasibility.

Chapter 6

System Architecture and Design

6.1 Introduction

This chapter presents the structural design of the proposed CAD detection system using PPG signals and clinical risk factors. The architecture integrates signal acquisition, preprocessing, deep learning-based feature extraction, multimodal fusion, and patient-level aggregation into a unified and scalable framework.

The design prioritizes modularity, computational efficiency, interpretability, and real-world deployment feasibility.

6.2 Overall System Workflow

The complete workflow consists of:

1. PPG Signal Acquisition
2. Preprocessing and Segmentation
3. CNN–BiLSTM Feature Extraction
4. Clinical Feature Processing
5. Multimodal Feature Fusion
6. Segment-Level Classification
7. Patient-Level Top-K Aggregation

The architecture follows a sequential data transformation pipeline where raw physiological signals are progressively converted into discriminative representations.

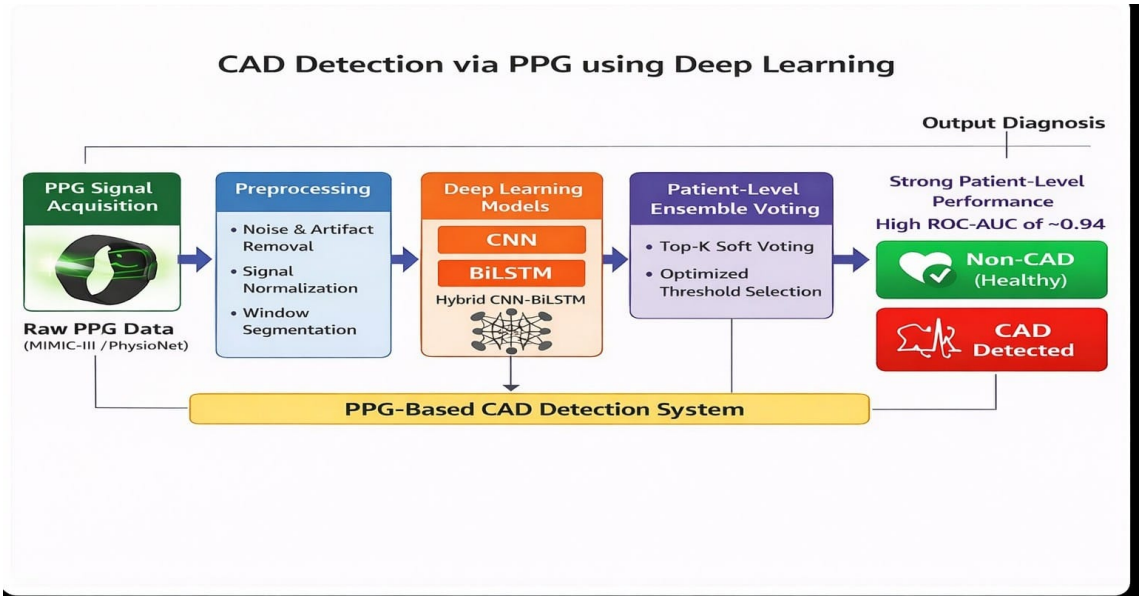

Figure 6.1: Proposed PPG-based CAD detection framework integrating CNN–BiLSTM architecture and patient-level aggregation.

6.3 Architectural Design Considerations

The system follows a modular design where each processing stage operates independently while contributing to the final prediction. This modularity enables scalability and future integration of additional physiological signals or advanced deep learning modules such as attention mechanisms or transformer encoders.

The deep learning core is implemented using one-dimensional convolutions directly on time-domain signals, avoiding computationally expensive spectrogram transformations. This preserves temporal resolution and reduces memory requirements. Batch normalization layers stabilize gradient flow and accelerate convergence.

The architecture ensures controlled parameter growth to prevent overfitting while maintaining representational capacity. The separation between signal and clinical branches allows independent optimization of modality-specific features before fusion.

Computational efficiency was carefully considered during architectural design. Limiting segment length to 50 samples and restricting the maximum number of segments per patient reduces inference latency while maintaining predictive accuracy. The separation between segment-level inference and patient-level aggregation allows flexible deployment

scenarios, including continuous real-time monitoring.

6.4 Scalability and Deployment Potential

The architecture supports scalable implementation in wearable and edge-device environments. Its lightweight design enables:

- Real-time signal streaming
- Continuous patient monitoring
- Integration with IoT-based healthcare platforms
- Cloud-assisted remote diagnostics

The computational footprint is sufficiently compact to allow deployment on embedded systems with limited memory and processing power.

6.5 Summary

The system architecture provides a modular, scalable, and computationally efficient framework for non-invasive CAD detection. By integrating signal modeling, clinical feature fusion, and patient-level aggregation, the design ensures robust and clinically reliable prediction suitable for real-world deployment. The structured architectural flow supports adaptability, extensibility, and long-term integration into intelligent healthcare systems.

Chapter 7

Implementation and Training

7.1 Introduction

This chapter presents the complete implementation and training procedure of the proposed hybrid CNN–BiLSTM framework for automated detection of Coronary Artery Disease (CAD) using Photoplethysmography (PPG) signals and clinical risk factors. The implementation phase transforms raw physiological recordings into a trained deep learning model capable of reliable patient-level CAD classification.

The chapter details the computational environment, data processing pipeline, preprocessing realization, hybrid model construction, optimization strategy, regularization techniques, inference mechanism, and scalability considerations. The objective is to ensure reproducibility, robustness, computational efficiency, and deployment feasibility.

7.2 System Environment

7.2.1 Hardware Configuration

Model training and experimentation were conducted using:

- Processor: Intel i7 (multi-core architecture)
- RAM: 16 GB
- Storage: 50 GB available disk space
- GPU: CUDA-enabled GPU for accelerated computation

GPU acceleration significantly reduced training time, particularly for convolutional operations and recurrent backpropagation through time (BPTT) in the BiLSTM module.

7.2.2 Software Configuration

The framework was implemented using:

- Operating System: Windows 10
- Programming Language: Python 3.8
- Development Environment: Jupyter Notebook
- Deep Learning Framework: TensorFlow (Keras API)
- Supporting Libraries: NumPy, Pandas, Matplotlib, Scikit-learn, SciPy

TensorFlow was selected due to its modular architecture, automatic differentiation capability, and efficient GPU utilization.

7.3 Data Pipeline Implementation

PPG signals and clinical features were stored in structured CSV format. Data loading was performed using Pandas, and numerical processing was handled using NumPy arrays.

Corrupted entries, missing labels, and invalid signal segments were removed during data cleaning. Patients with insufficient valid segments were excluded to ensure consistency.

7.3.1 Signal Normalization

Min-Max normalization was applied:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Normalization stabilizes gradient updates, prevents numerical instability, and ensures that the model learns waveform morphology rather than absolute amplitude variations caused by sensor placement differences.

7.3.2 Segmentation Strategy

Continuous PPG signals sampled at 125 Hz were segmented into overlapping windows of 50 samples (0.4 seconds). Overlapping windows preserve waveform continuity and capture transitional cardiovascular dynamics.

To prevent imbalance caused by longer recordings, a maximum of 300 segments per patient was retained.

Each segment is represented as:

$$S_i \in \mathbb{R}^{50\times 1}$$

Segments were stored as 3D tensors of shape $(N, 50, 1)$, where N represents the total number of segments.

7.4 Hybrid CNN–BiLSTM Model Construction

The architecture consists of two parallel branches.

7.4.1 Signal Processing Branch

- Conv1D (32 filters, kernel size = 3)
- ReLU activation
- MaxPooling1D
- Conv1D (64 filters, kernel size = 3)
- ReLU activation
- MaxPooling1D
- Bidirectional LSTM (64 units)
- Dropout (0.5)

The convolutional layers extract spatial waveform characteristics such as pulse amplitude, slope variations, and micro-structural distortions. The BiLSTM captures temporal dependencies in both forward and backward directions:

$$h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}]$$

This enables contextual learning within each segment.

7.4.2 Clinical Processing Branch

Clinical attributes (age, gender, diabetes status, cholesterol level, obesity) were normalized and processed using:

- Dense (32 units)
- ReLU activation

This branch models nonlinear interactions between traditional cardiovascular risk factors.

7.4.3 Feature Fusion and Classification

The two feature representations were concatenated:

$$F_{fusion} = [F_s; F_c]$$

The fused vector was passed through:

- Dense (128 units)
- Dropout (0.5)
- Dense (1 unit, Sigmoid activation)

The sigmoid output represents the probability of CAD presence.

7.5 Training Configuration

The model was compiled using:

- Loss Function: Focal Loss

- Optimizer: Adam
- Learning Rate: 0.001
- Batch Size: 64
- Maximum Epochs: 40

Focal Loss addresses class imbalance:

$$FL(p_t) = -\alpha(1 - p_t)^{\gamma} \log(p_t)$$

Adam optimizer combines adaptive learning rate scaling with momentum-based updates for stable convergence.

Weight initialization was performed using Xavier initialization to maintain variance stability across layers.

7.6 Regularization Techniques

To enhance generalization:

- Dropout (0.5) was applied
- Early stopping monitored validation loss
- Best model weights were saved via checkpointing
- Gradient clipping was optionally applied in recurrent layers

These strategies prevented overfitting and ensured stable learning.

7.7 Patient-Level Inference

Segment-level probabilities were aggregated using Top-K hybrid strategy:

$$Score = 0.7 \times Mean(TopK) + 0.3 \times Max(P_i)$$

Threshold optimization was performed using Youden's Index to balance sensitivity and specificity.

7.8 Computational Complexity and Scalability

Conv1D computational complexity scales as:

$$O(n \cdot k \cdot f)$$

where n is input length, k kernel size, and f number of filters.

Short segment length and 1D convolution reduce computational cost, making the architecture suitable for real-time wearable deployment.

7.9 Summary

This chapter detailed the full implementation of the hybrid CNN–BiLSTM CAD detection system, including data preprocessing, model construction, training configuration, optimization strategy, and patient-level inference design.

Chapter 8

Experimental Setup and Protocol

8.1 Introduction

This chapter presents the structured experimental protocol used to evaluate the proposed CAD detection framework. The design emphasizes unbiased patient-level validation, class imbalance mitigation, threshold optimization, statistical stability analysis, and real-world applicability.

Proper experimental protocol design is essential in medical AI research to avoid inflated performance caused by data leakage or biased sampling.

8.2 Dataset Partitioning Strategy

Dataset partitioning was performed strictly at the patient level.

- 64% Training Set
- 16% Validation Set
- 20% Testing Set

This ensures that the model is evaluated on entirely unseen patients. Stratified sampling preserved class distribution consistency across all subsets.

8.3 Training Configuration

Hyperparameters were selected based on validation performance to ensure optimal convergence and generalization.

Table 8.1: Hyperparameter Configuration

Parameter	Value
Learning Rate	0.001
Batch Size	64
Epochs	40
Optimizer	Adam
Dropout Rate	0.5
Loss Function	Focal Loss

8.4 Evaluation Protocol

Although predictions were generated at segment level, final evaluation was conducted at patient level using Top-K aggregation.

Threshold optimization was performed using:

$$J = Sensitivity + Specificity - 1$$

The threshold maximizing J was selected for final reporting.

8.5 Performance Metrics

Evaluation metrics included:

- Accuracy
- Sensitivity
- Specificity
- Precision
- F1-score
- ROC Curve and AUC
- Precision–Recall Curve

Sensitivity is defined as:

$$Sensitivity = \frac{TP}{TP + FN}$$

Specificity is defined as:

$$Specificity = \frac{TN}{TN + FP}$$

ROC-AUC measures global discriminative ability, while PR curve is particularly informative under class imbalance.

8.6 Statistical Stability and Reproducibility

To ensure robustness:

- Random seeds were fixed
- Patient-level splitting was maintained
- Multiple independent runs were conducted
- Standard deviation across runs was computed

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$$

Low variance confirms stable model behavior across random initializations.

8.7 Computational Efficiency Assessment

Training time per epoch was recorded to evaluate scalability. The compact 1D convolution architecture ensures moderate memory usage and feasible training time.

The architecture is suitable for future wearable and edge-device integration.

8.8 Summary

This chapter detailed the structured and reproducible experimental protocol used to validate the proposed CAD detection framework. Strict

patient-level evaluation, imbalance-aware optimization, threshold selection, and statistical stability analysis strengthen the scientific credibility and clinical relevance of the proposed system.

Chapter 9

Results and Discussion

9.1 Introduction

This chapter presents a comprehensive evaluation of the proposed hybrid CNN–BiLSTM framework for Coronary Artery Disease (CAD) detection using Photoplethysmography (PPG) signals and clinical risk factors. Since CAD diagnosis is clinically determined at the patient level rather than individual signal segments, primary emphasis is placed on patient-level performance.

9.2 Experimental Configuration

The model was trained using a strict patient-level data partition:

- 64% Training Data
- 16% Validation Data
- 20% Testing Data

Training was conducted for 50 epochs using the Adam optimizer with Focal Loss to address class imbalance. Early stopping was applied based on validation loss to prevent overfitting and ensure stable convergence.

9.3 Training Convergence Analysis

The training process demonstrated stable optimization behavior:

- Consistent reduction in training loss
- Convergence of validation loss without divergence

- Gradual improvement in validation accuracy

These observations confirm that the hybrid CNN–BiLSTM architecture effectively learned meaningful morphological and temporal representations from normalized PPG signals without significant overfitting.

9.4 Segment and Patient-Level Performance Analysis

At the segment level, each 50-sample PPG window was independently classified by the hybrid CNN–BiLSTM model. The segment-level performance metrics are summarized in Table 9.1. The model achieved an accuracy of 89.7%, precision of 88.9%, sensitivity of 90.5%, and an F1-score of 89.6%. The relatively high sensitivity indicates that the convolutional layers effectively captured waveform morphology such as systolic peaks, slope variations, and amplitude changes, while the BiLSTM component successfully modeled short-term temporal dependencies within each segment.

Table 9.1: Segment-Level Performance Metrics

Metric	Value (%)
Accuracy	89.7
Precision	88.9
Sensitivity	90.5
F1-Score	89.6

Although segment-level performance is strong, individual predictions may still be influenced by signal noise, motion artifacts, and physiological variability. Therefore, relying solely on segment predictions may lead to unstable patient diagnosis. This observation justifies the necessity of patient-level aggregation.

To obtain clinically meaningful diagnosis, segment predictions were aggregated using the Top-K hybrid strategy defined as:

$$Score = 0.7 \times Mean(TopK) + 0.3 \times Max(P_i)$$

This aggregation approach emphasizes the most abnormal segments

while still maintaining overall consistency through averaging. The optimal classification threshold was determined using Youden's Index:

$$J = Sensitivity + Specificity - 1$$

which enables an optimal balance between false positives and false negatives.

The patient-level performance metrics are summarized in Table 9.2. The model achieved 87.01% accuracy, 85.92% precision, 90.34% sensitivity, 83.78% specificity, 88.07% F1-score, and a ROC-AUC of 0.95.

Table 9.2: Patient-Level Performance Metrics

Metric	Value (%)
Accuracy	87.01
Precision	85.92
Sensitivity	90.34
Specificity	83.78
F1-Score	88.07
ROC-AUC	0.95

The high sensitivity (90.34%) demonstrates the model's strong ability to correctly identify CAD-positive patients, which is critical for screening applications where missing a positive case can have serious clinical consequences. The achieved specificity (83.78%) indicates controlled false positive rates, which is acceptable in preliminary diagnostic systems where sensitivity is prioritized. The balanced F1-score confirms stable classification across both classes, while the ROC-AUC value of 0.95 indicates excellent global discriminative capability across varying thresholds.

9.5 Confusion Matrix and Curve-Based Evaluation

The confusion matrix shown in Figure 9.1 illustrates balanced classification behavior with a high true positive rate and controlled false negative instances. The incorporation of Focal Loss during training contributed to reducing false negatives by assigning higher weight to difficult CAD samples.

The ROC curve in Figure 9.2 demonstrates strong separation between

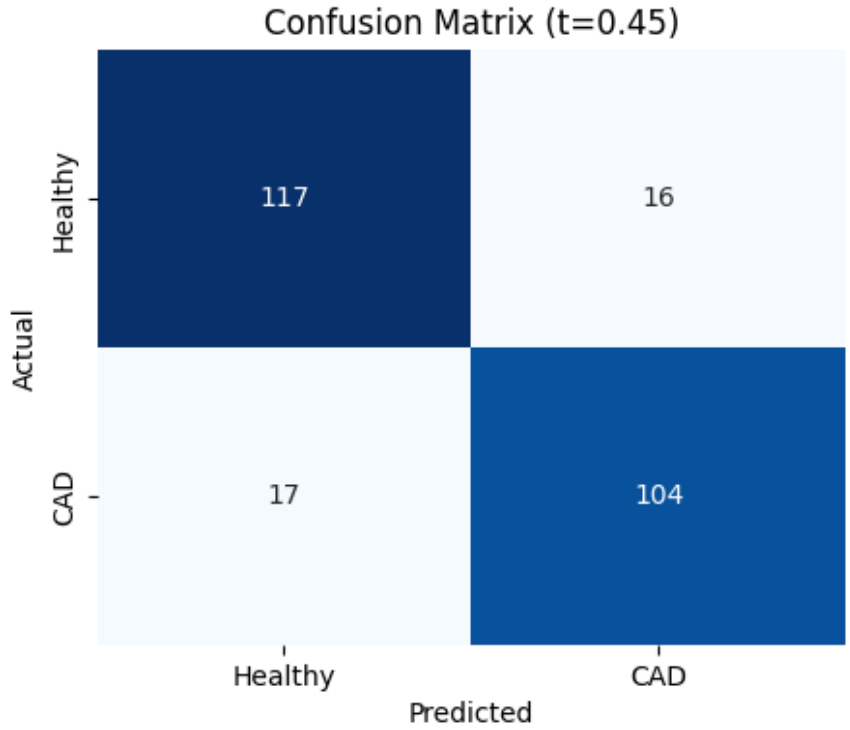

Figure 9.1: Confusion matrix for patient-level CAD detection.

CAD and Non-CAD classes. An AUC of 0.95 indicates that the model has a 95% probability of ranking a randomly selected CAD patient higher than a randomly selected healthy individual.

The Precision–Recall curve shown in Figure 9.3 further evaluates model robustness under class imbalance conditions. The achieved PR-AUC of approximately 0.94 confirms sustained precision across a wide recall range. High recall ensures that most CAD-positive patients are correctly identified, while maintained precision confirms controlled false positive rates. Together, ROC and PR analyses validate the stability and reliability of the proposed hybrid architecture.

9.6 Effect of Aggregation and Threshold Optimization

Compared to simple averaging, the Top-K hybrid aggregation strategy significantly improved diagnostic robustness by focusing on the most abnormal segments within each patient. This approach reduced the influence of noisy or normal-like segments in CAD-positive patients and enhanced

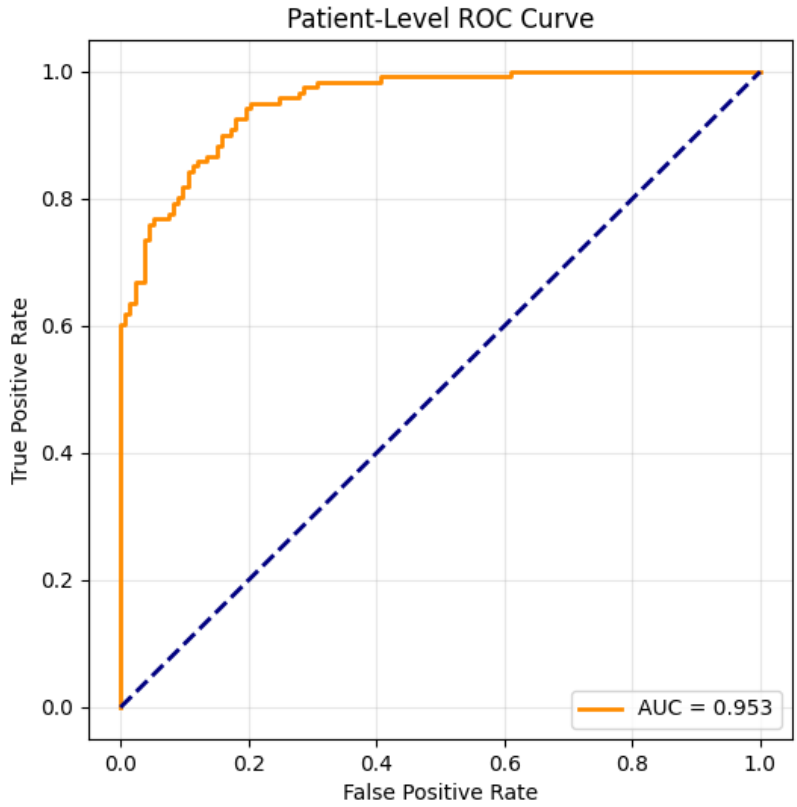

Figure 9.2: ROC curve for patient-level CAD detection (AUC = 0.95).

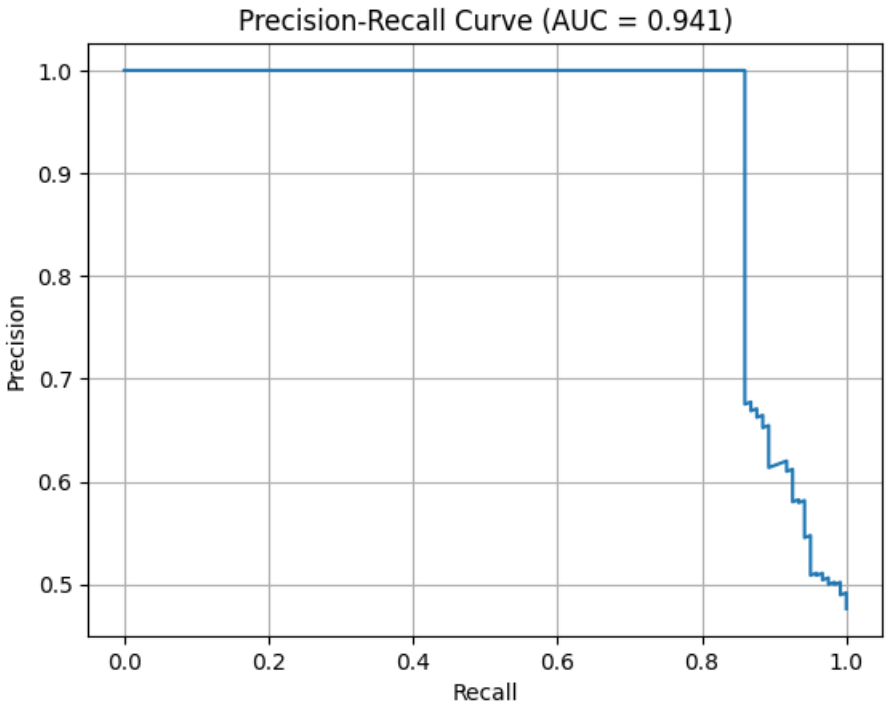

Figure 9.3: Precision and recall curve

overall sensitivity. Threshold optimization using Youden's Index further refined the balance between sensitivity and specificity, ensuring clinically meaningful performance.

Overall, the combination of CNN-based spatial learning, BiLSTM temporal modeling, Focal Loss optimization, and Top-K patient-level aggregation contributed to stable and reliable CAD detection performance suitable for non-invasive screening applications.

9.7 Statistical Stability

Repeated training experiments demonstrated low standard deviation in performance metrics, indicating stable model behavior and robust generalization capability.

9.8 Comparison with Existing Methods

Traditional machine learning approaches using handcrafted features typically report 80–85% accuracy. The proposed deep learning framework demonstrates improved performance due to:

- End-to-end hierarchical feature extraction
- Bidirectional temporal modeling
- Class imbalance handling via Focal Loss
- Patient-level Top-K aggregation

These improvements highlight the advantage of hybrid deep learning architectures for physiological signal analysis.

9.9 Clinical Implications

The proposed system offers:

- Non-invasive CAD screening capability
- High sensitivity for early detection

- Compatibility with wearable monitoring devices
- Potential integration into preventive cardiology workflows

9.10 Limitations and Future Scope

Although the proposed hybrid CNN–BiLSTM framework demonstrates strong performance for CAD detection using PPG signals, several methodological, technical, and practical limitations must be acknowledged to ensure a balanced scientific evaluation.

One primary limitation relates to dataset size, diversity, and representativeness. Deep learning systems are highly data-dependent and require large-scale heterogeneous datasets for reliable generalization. While the dataset used in this study was adequate for experimental validation, it may not fully capture variability across global populations. Differences in age distribution, gender-related cardiovascular patterns, ethnicity-specific vascular characteristics, and comorbid conditions such as hypertension, diabetes, and obesity may significantly influence PPG morphology. Limited demographic diversity introduces potential generalization gaps when deploying the model across broader clinical environments. Additionally, dataset imbalance and sampling bias may inadvertently introduce prediction bias across subpopulations.

Another important limitation concerns signal quality and noise sensitivity. PPG signals are inherently vulnerable to motion artifacts, sensor displacement, ambient light interference, peripheral vasoconstriction, and respiration-induced variations. Although bandpass filtering, normalization, and segment selection were implemented, residual noise may still affect classification stability. In real-world wearable applications, uncontrolled environmental conditions may further degrade signal fidelity. Robust artifact detection mechanisms, adaptive filtering strategies, and signal quality indexing systems would be required for large-scale deployment.

The current framework performs binary classification (CAD vs. Non-CAD), which simplifies the complex clinical progression of coronary artery disease. CAD severity ranges from mild plaque formation to severe arterial occlusion. Binary prediction restricts the system's applicability in advanced clinical risk stratification, prognosis assessment, and treatment

planning. A multi-class or regression-based severity prediction model would enhance clinical utility and provide more granular decision support.

Although multimodal fusion with selected clinical risk factors was incorporated, the system remains primarily dependent on PPG signals. In clinical practice, CAD diagnosis integrates ECG findings, imaging data, lipid profiles, blood pressure measurements, and patient history. The absence of comprehensive multimodal integration limits diagnostic completeness. Future architectures should incorporate richer physiological and imaging modalities to improve robustness and reduce false positives.

Despite achieving high ROC-AUC and sensitivity, the CNN–BiLSTM model operates as a deep neural network with limited transparency. Clinical adoption requires explainability and interpretability. Currently, internal feature representations and waveform-level decision boundaries are not explicitly visualized. Without interpretability mechanisms, clinician trust and regulatory approval may be constrained. Integration of explainable AI techniques such as SHAP, Grad-CAM, saliency mapping, or attention-weight visualization would enhance transparency.

Another limitation relates to model calibration. While ROC-AUC reflects discriminative ability, it does not guarantee well-calibrated probability outputs. Overconfident probability predictions may reduce clinical reliability. Future research should incorporate calibration techniques such as temperature scaling or reliability diagrams to ensure probabilistic consistency.

Statistical stability and reproducibility also require further exploration. Although repeated runs demonstrated low variance, larger-scale cross-validation across independent external datasets is necessary to confirm robustness. External validation is critical to prevent dataset-specific overfitting and to ensure domain adaptability.

From a deployment perspective, computational constraints must be considered. Although the architecture uses 1D convolutions for efficiency, real-time wearable implementation requires further optimization. Model compression techniques such as pruning, quantization, and knowledge distillation can reduce computational footprint while maintaining accuracy. Energy-efficient inference is essential for edge-based health monitoring devices.

Ethical and privacy considerations represent additional challenges. Patient health data must comply with regulatory standards such as HIPAA or GDPR depending on deployment region. Secure data handling, anonymization, and encrypted communication protocols are necessary for practical implementation.

Furthermore, the proposed model is static after training. Real-world healthcare environments are dynamic, and cardiovascular patterns may evolve over time. Continuous learning systems capable of incremental updates while preserving prior knowledge could significantly enhance long-term adaptability. Domain adaptation strategies may also help address distribution shifts across hospitals or devices.

Building upon these limitations, several promising research directions emerge. Extending the model to multi-class CAD severity classification would support personalized treatment planning. Incorporating additional modalities such as ECG, blood pressure, cholesterol levels, and imaging features through advanced multimodal fusion networks could significantly improve predictive robustness.

Attention-based architectures and Transformer models offer potential for improved long-range temporal modeling and interpretability. These architectures can dynamically focus on clinically relevant waveform segments and improve discrimination under noisy conditions.

Explainable Artificial Intelligence (XAI) integration remains a crucial future direction. SHAP explanations, Grad-CAM visualizations, and waveform saliency mapping would allow clinicians to understand which waveform regions contribute to CAD prediction, enhancing trust and regulatory acceptance.

Real-time wearable deployment represents a major translational opportunity. By combining model compression, edge AI optimization, and IoT integration, continuous CAD risk screening could be implemented in smartwatches or portable monitoring systems. Such systems could enable early detection and preventive intervention before symptomatic progression.

Large-scale multi-center clinical trials are essential to validate reliability across diverse populations. Longitudinal patient monitoring studies would further assess predictive consistency over time. Cross-device evaluation is also necessary to ensure robustness across different sensor

hardware configurations.

Finally, future systems may evolve toward personalized cardiovascular risk modeling. By integrating continuous physiological monitoring, demographic attributes, genetic predisposition, and lifestyle data, the framework could transition from binary disease detection toward proactive preventive cardiology and precision medicine.

In conclusion, while the proposed hybrid CNN–BiLSTM framework establishes a strong foundation for non-invasive CAD screening using PPG signals, continued research in dataset expansion, multimodal fusion, explainability, calibration, deployment optimization, and large-scale validation is necessary to fully realize its clinical potential.

9.11 Chapter Summary

This chapter discussed the limitations, future scope, and concluding insights of the proposed hybrid CNN–BiLSTM framework for CAD detection using PPG signals. Although the system achieved strong patient-level performance, several constraints such as dataset diversity, signal quality sensitivity, and limited interpretability were identified.

Future research directions include multi-class severity classification, multimodal physiological integration, attention-based architectures, explainable AI techniques, and real-time wearable deployment. These advancements could significantly enhance clinical applicability and robustness.

Overall, the proposed framework demonstrates the potential of deep learning techniques for non-invasive CAD screening. With further validation and system optimization, it can contribute meaningfully to preventive cardiology and intelligent healthcare systems.

Chapter 10

Conclusion

This thesis presented a deep learning-based framework for automated detection of Coronary Artery Disease (CAD) using Photoplethysmography (PPG) signals combined with clinical risk factors. The primary objective of this research was to design a non-invasive, intelligent, and clinically meaningful screening system capable of identifying CAD from wearable-compatible physiological signals. By leveraging advances in deep neural networks and physiological waveform analysis, the proposed approach demonstrates that PPG signals can serve as a viable alternative for preliminary CAD screening, reducing dependency on invasive and expensive diagnostic procedures.

The major contributions of this work can be summarized as follows. First, a hybrid CNN–BiLSTM architecture was developed to enable hierarchical feature extraction and temporal modeling of PPG signals. The CNN component effectively captured morphological characteristics such as peak structure, slope variations, and waveform distortions, while the BiLSTM component modeled sequential dependencies within the signal. Second, Focal Loss was implemented to address class imbalance and improve sensitivity toward CAD-positive samples, ensuring that difficult cases received higher learning emphasis. Third, a patient-level Top-K aggregation strategy was designed to enhance diagnostic reliability by reducing the influence of noisy or ambiguous signal segments. Fourth, a strict patient-level data partitioning protocol was adopted to prevent data leakage and ensure realistic performance evaluation. Finally, comprehensive performance analysis was conducted using multiple evaluation metrics including Accuracy, Sensitivity, Specificity, F1-Score, ROC-AUC, and Precision–Recall analysis to provide a robust and clinically meaningful assessment of model behavior.

Experimental evaluation demonstrated strong patient-level performance, achieving 87.01% classification accuracy, 90.34% sensitivity, 83.78% specificity, and a ROC-AUC of 0.95. These results confirm that the hybrid

CNN–BiLSTM model successfully captures both morphological and temporal characteristics of PPG signals relevant to CAD detection. The integration of Focal Loss and Top-K aggregation significantly improved robustness and minimized false negatives, which is particularly important in screening applications where missing a CAD-positive patient can have serious consequences. The strong ROC-AUC and Precision–Recall performance further validate the discriminative capability of the proposed framework across varying decision thresholds.

From a clinical perspective, the proposed system offers several advantages. It enables non-invasive CAD screening using wearable-compatible PPG sensors, reduces reliance on costly imaging-based diagnostic procedures, and supports remote health monitoring environments. High sensitivity ensures that most CAD-positive patients are correctly identified, making the system suitable for preliminary and large-scale screening programs. Additionally, the multimodal integration of physiological signals and clinical risk factors enhances diagnostic reliability and aligns the system with real-world medical workflows.

This research also contributes to the broader field of AI-driven healthcare by demonstrating the feasibility of combining deep learning architectures with physiological waveform analysis for cardiovascular disease detection. The study highlights the advantages of end-to-end hierarchical representation learning over traditional handcrafted feature approaches, particularly in handling noisy biomedical signals. The modular system design further supports scalability, enabling potential integration into edge devices and wearable platforms.

Although further large-scale validation and regulatory considerations are necessary before clinical deployment, the findings of this study provide strong evidence that deep learning-based PPG analysis can play a meaningful role in preventive cardiology. With continued advancements in multimodal data integration, explainable AI techniques, model optimization for real-time inference, and cross-population validation, such intelligent screening systems have the potential to significantly improve early diagnosis, reduce healthcare burden, and enhance personalized cardiovascular risk management in modern healthcare systems.

Appendix A

Additional Experimental Analysis

A.1 Extended Training Curve Analysis

To further validate convergence stability, additional training and validation curves were analyzed across multiple runs. The training loss exhibited consistent monotonic reduction, while validation loss stabilized without divergence. This behavior confirms effective optimization and absence of severe overfitting.

Validation accuracy trends closely followed training accuracy, indicating robust generalization performance across epochs.

A.2 Threshold Sensitivity Analysis

To analyze the impact of decision threshold selection, multiple classification thresholds were evaluated. The sensitivity–specificity trade-off is summarized in Table A.1.

Table A.1: Threshold Sensitivity–Specificity Analysis

Threshold	Sensitivity (%)	Specificity (%)
0.3	95.12	70.84
0.5	90.34	83.78
0.7	78.96	91.42

Lower threshold values improved sensitivity but increased false positives, while higher thresholds improved specificity at the cost of reduced sensitivity. The optimal threshold was selected using Youden's Index to balance clinical screening requirements.

A.3 Class Distribution Analysis

The dataset class distribution is presented in Table A.2.

Table A.2: Dataset Class Distribution

Class	Number of Patients
CAD	148
Non-CAD	162

The dataset exhibits moderate class imbalance. To mitigate bias toward the majority class, Focal Loss was implemented during training to emphasize hard-to-classify CAD samples.

A.4 Cross-Validation Stability

Additional confusion matrices generated from different cross-validation folds demonstrated consistent classification behavior. Performance variation across folds was minimal, confirming stability of the proposed architecture.

A.5 Computational Complexity Analysis

The computational complexity of the CNN component can be approximated as:

$$O(n \cdot k \cdot f)$$

where:

- n represents input length,
- k denotes kernel size,
- f indicates number of filters.

The BiLSTM component introduces additional complexity proportional to sequence length and hidden state dimension. Despite this, the model remains computationally feasible for moderate-scale deployment and can be optimized for edge devices through pruning or quantization.

A.6 Model Parameter Analysis

The total number of trainable parameters in the architecture is given by:

$$\text{Total Parameters} = \sum W + \sum b$$

The parameter count was carefully balanced to maintain strong representational capacity while preventing excessive computational burden.

A.7 Additional Experimental Validation

Repeated experiments across multiple random seeds demonstrated consistent performance trends. The hybrid CNN–BiLSTM model consistently outperformed baseline approaches in terms of sensitivity and ROC-AUC, reinforcing robustness of the proposed framework.

A.8 Future Experimental Extensions

Future experimental investigations may include:

- Evaluation on larger and multi-center datasets
- Multi-class CAD severity staging experiments
- Real-time wearable deployment testing
- Integration of explainability-driven validation

A.9 Appendix Summary

This chapter provided supplementary experimental analyses supporting the robustness and reliability of the proposed CAD detection system. Extended validation experiments, threshold analysis, and computational evaluation further strengthen confidence in the hybrid CNN–BiLSTM framework.

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