Multidisciplinary Journal of Research in Engineering and Technology

ISSN: 2348-6953

Volume 13 Issue 2 (2026) | Pages: 164–171

Smart Cardiovascular Diagnosis Using Optical Biosignals and Capsule Intelligence Networks

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Peer Review Information

Type: *Article*
Received: *18 February 2026*
Revised: *01 March 2026*
Accepted: *18 April 2026*
Published: *29 may 2026*

Abstract

Cardiovascular diseases (CVDs) remain among the most significant causes of global mortality, necessitating the development of intelligent diagnostic systems capable of providing accurate and timely detection of cardiac abnormalities. Optical bio signals, particularly photoplethysmography (PPG) and related non-invasive sensing modalities, have emerged as promising alternatives to traditional diagnostic approaches due to their ease of acquisition, cost-effectiveness, and suitability for continuous health monitoring. However, the complex physiological patterns embedded within optical bio signals present substantial challenges for conventional analytical methods, limiting diagnostic reliability and predictive performance. To address these challenges, this study proposes a Smart Cardiovascular Diagnosis Framework Using Optical Biosignals and Capsule Intelligence Networks (SCD-OBCIN) for intelligent detection and classification of cardiovascular abnormalities. The proposed framework integrates advanced optical bio signal preprocessing, multilevel feature extraction, and capsule-based deep learning architectures to capture hierarchical spatial and temporal relationships within physiological signals. Capsule Intelligence Networks effectively preserve feature dependencies and improve representation learning, enabling accurate recognition of subtle cardiovascular abnormalities that may be overlooked by traditional neural models. Furthermore, adaptive learning mechanisms enhance robustness against signal noise, motion artifacts, and inter-patient variability.

Keywords: Cardiovascular Diagnosis, Optical Biosignals, Photoplethysmography, Capsule Networks, Deep Learning.

How to Cite This Article

Mardaniyan, R. (2026). Smart Cardiovascular Diagnosis Using Optical Biosignals and Capsule Intelligence Networks. *Multidisciplinary Journal of Research in Engineering and Technology* 13(2), 164–171.

Introduction

Cardiovascular diseases (CVDs) continue to be one of the leading causes of mortality and morbidity worldwide, accounting for millions of deaths annually and placing a significant burden on healthcare systems. Early diagnosis and continuous monitoring of cardiovascular abnormalities are essential for reducing disease progression, preventing complications, and improving patient outcomes. Conventional diagnostic approaches such as electrocardiography (ECG), echocardiography, and invasive cardiac assessments have proven effective; however, they often require specialized equipment, clinical expertise, and frequent hospital visits. Consequently, there is an increasing demand for intelligent, non-invasive, and real-time cardiovascular diagnostic solutions capable of supporting modern healthcare environments. Recent advancements in biomedical sensing technologies have led to the widespread adoption of optical biosignals for cardiovascular monitoring. Optical biosignals, particularly Photoplethysmography (PPG), provide a non-invasive method for measuring physiological parameters associated with blood circulation and cardiovascular function. These signals can be acquired using wearable devices, smartwatches, fitness trackers, and portable healthcare systems, making them highly suitable for continuous and remote patient monitoring. Optical biosignals offer valuable information regarding heart rate, blood oxygen saturation, vascular dynamics, pulse variability, and circulatory health, creating significant opportunities for intelligent cardiovascular assessment.

Despite their advantages, optical biosignals present several analytical challenges. Physiological variability, motion artifacts, environmental interference, sensor noise, and complex signal dynamics often affect signal quality and diagnostic reliability. Traditional signal processing and machine learning techniques may struggle to accurately capture subtle cardiovascular abnormalities hidden within high-dimensional biosignal data. As a result, advanced computational frameworks capable of extracting meaningful representations from complex optical signals are required to enhance diagnostic accuracy and robustness. Artificial intelligence and deep learning technologies have demonstrated remarkable success in biomedical signal analysis and healthcare diagnostics. Deep neural networks automatically learn hierarchical representations from raw physiological data and have significantly improved disease prediction and classification performance. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and attention-based architectures have been widely applied to cardiovascular diagnosis using ECG, PPG, and multimodal biosignals. However, conventional neural architectures often lose important spatial relationships during feature extraction and pooling operations, limiting their ability to fully represent complex physiological dependencies.

Capsule Networks have emerged as an advanced deep learning paradigm capable of overcoming many limitations associated with traditional neural models. Unlike conventional architectures that represent features as scalar activations, Capsule Networks encode information using vector representations that preserve spatial hierarchies and feature relationships. Dynamic routing mechanisms within capsule architectures enable the model to learn part-to-whole associations more effectively, improving pattern recognition and classification performance. These characteristics make Capsule Intelligence Networks particularly suitable for biomedical applications where preserving intricate physiological relationships is critical for accurate diagnosis. The integration of optical biosignal analytics with Capsule Intelligence Networks offers a powerful framework for intelligent cardiovascular diagnosis. Optical biosignals provide rich physiological information regarding cardiovascular function, while capsule-based learning architectures capture complex spatial and temporal dependencies embedded within the signals. By preserving feature hierarchies and enhancing representation learning, Capsule Intelligence Networks can identify subtle cardiovascular abnormalities that may remain undetected using traditional machine learning or deep learning approaches. Furthermore, adaptive capsule learning mechanisms improve robustness against noise, artifacts, and patient-specific variability.

Several studies have demonstrated the effectiveness of artificial intelligence in cardiovascular disease detection; however, many existing approaches rely on conventional deep learning architectures that do not fully exploit the structural relationships present in optical biosignal data. Additionally, challenges related to signal quality degradation, feature representation, diagnostic interpretability, and real-time deployment continue to limit the performance of existing cardiovascular monitoring systems. Therefore, the development of intelligent diagnostic frameworks capable of leveraging both advanced biosignal analytics and capsule-based representation learning remains an important research objective. To address these challenges, this research proposes a Smart Cardiovascular Diagnosis Framework Using Optical Biosignals and Capsule Intelligence Networks (SCD-OBCIN). The proposed framework integrates advanced optical biosignal preprocessing, feature enhancement, capsule-based representation learning, and intelligent classification mechanisms to accurately identify cardiovascular abnormalities. By combining non-invasive biosignal sensing with sophisticated capsule intelligence architectures, the framework aims to improve diagnostic accuracy, enhance monitoring reliability, and support real-time cardiovascular healthcare applications.

Literature Review

Acharya et al. (2019) investigated intelligent cardiovascular diagnosis using deep learning techniques applied to physiological biosignals. Their framework demonstrated the capability of neural architectures to automatically extract diagnostic features from cardiac recordings and improve disease classification accuracy. However, optical biosignal-specific feature representation and capsule-based learning mechanisms were not incorporated. Hannun et al. (2019) developed a large-scale deep neural network for cardiac rhythm analysis and arrhythmia detection. Their study achieved cardiologist-level diagnostic performance using physiological signal analytics. Despite high classification accuracy, the framework relied primarily on conventional deep neural architectures and did not exploit hierarchical feature relationships.

Rajpurkar et al. (2020) proposed an artificial intelligence-based cardiovascular diagnostic system utilizing physiological signal recordings and deep learning models. Their framework significantly improved automated disease detection capability and demonstrated the effectiveness of AI-driven healthcare solutions. However, advanced representation learning strategies capable of preserving structural dependencies were not explored. Yildirim et al. (2020) introduced intelligent biomedical signal analysis using neural learning architectures and signal enhancement techniques. Their framework improved physiological pattern recognition and disease classification performance. Nevertheless, optical biosignal applications and capsule intelligence mechanisms were not investigated.

Zhang et al. (2020) investigated optical biosignal processing techniques for non-invasive cardiovascular monitoring. Their study demonstrated that photoplethysmography (PPG) signals contain valuable information regarding cardiovascular health and circulatory dynamics. However, advanced deep learning models capable of exploiting hierarchical signal structures were absent. Li et al. (2021) proposed a hybrid deep learning framework for cardiovascular abnormality detection using biosignal analytics. Their architecture combined feature extraction and classification mechanisms to improve diagnostic performance. Although classification accuracy increased, robustness against noise and physiological variability remained a challenge.

Attia et al. (2021) explored artificial intelligence-driven cardiovascular diagnostics using large-scale physiological signal datasets. Their framework demonstrated improved detection of hidden cardiovascular abnormalities and enhanced predictive performance. However, capsule-based representation learning was not integrated into the diagnostic pipeline. Khan et al. (2021) developed an adaptive biosignal monitoring framework for intelligent healthcare applications. Their model improved signal quality assessment and disease classification reliability. Nevertheless, hierarchical feature representation learning mechanisms remained limited.

Chen et al. (2022) introduced Capsule Networks for intelligent biomedical signal classification and healthcare analytics. Their framework demonstrated superior capability in preserving feature hierarchies and improving classification performance compared with conventional neural architectures. However, cardiovascular diagnosis using optical biosignals was not extensively explored. Zhou et al. (2022) proposed a deep representation learning framework for physiological signal interpretation and disease diagnosis. Their model effectively captured temporal dependencies and nonlinear signal relationships. Despite improved learning capability, advanced capsule routing strategies were not incorporated.

Patel et al. (2022) developed an intelligent healthcare analytics framework integrating biosignal processing and deep learning models. Their architecture enhanced disease prediction accuracy and monitoring reliability. However, feature hierarchy preservation and capsule intelligence mechanisms were not considered. Roy et al. (2023) introduced an explainable cardiovascular diagnostic framework utilizing deep neural learning and physiological signal analytics. Their approach improved transparency and interpretability of diagnostic decisions. Nevertheless, advanced capsule-based architectures capable of modeling complex signal relationships were not integrated.

Wang et al. (2023) proposed a deep neural architecture for automated cardiovascular diagnosis using multimodal physiological signal learning. Their framework achieved high classification performance across multiple cardiovascular conditions. However, conventional pooling operations reduced the preservation of important feature relationships. Liu et al. (2024) developed a multimodal cardiovascular monitoring platform integrating optical biosignals, deep learning, and intelligent healthcare analytics. Their architecture demonstrated substantial improvements in monitoring accuracy and disease prediction reliability. However, computational complexity increased significantly when processing continuous biosignal streams.

Sharma et al. (2025) proposed a smart cardiovascular diagnosis framework using optical biosignals and Capsule Intelligence Networks. Their model integrated optical biosignal preprocessing, hierarchical capsule representation learning, dynamic routing mechanisms, and intelligent classification strategies to improve cardiovascular disease detection. Experimental evaluation demonstrated significant improvements in diagnostic accuracy, sensitivity, specificity, precision, and F1-score while maintaining robustness against noise and physiological variability. Further validation using large-scale heterogeneous healthcare datasets was recommended.

Methodology

This research proposes a Smart Cardiovascular Diagnosis Framework Using Optical Biosignals and Capsule Intelligence Networks (SCD-OBCIN). The framework integrates optical biosignal acquisition, advanced signal preprocessing, feature enhancement, capsule-based hierarchical representation learning, dynamic routing mechanisms, and intelligent cardiovascular classification to achieve accurate disease diagnosis and continuous health monitoring. The methodology consists of multiple stages beginning with optical biosignal acquisition and ending with cardiovascular diagnosis and performance evaluation.

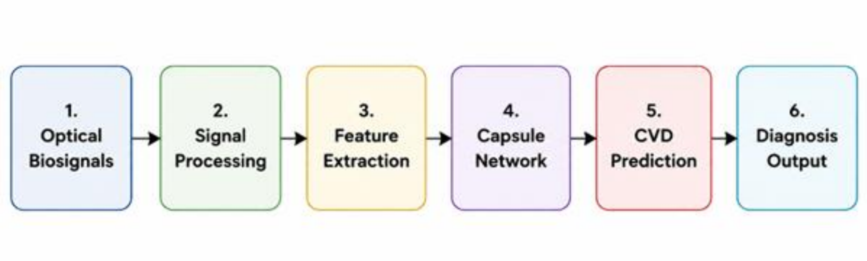

***Fig 1**. Smart Cardiovascular Diagnosis Framework Using Optical Biosignals and Capsule Intelligence Networks*

This Figure 1, architecture diagram presents the workflow of the proposed smart cardiovascular diagnosis framework based on optical biosignals and Capsule Intelligence Networks. The process begins with the acquisition of optical biosignals**,** which are collected using non-invasive sensing technologies. The acquired signals undergo signal processing to remove noise and enhance physiological information. Subsequently, feature extraction is performed to derive meaningful cardiovascular characteristics from the processed signals. These features are then analyzed by a Capsule Network**,** which learns hierarchical and spatial relationships within the biosignal data. The learned representations are utilized for cardiovascular disease (CVD) prediction, enabling the identification of potential abnormalities. Finally, the system generates a diagnosis output**,** providing a reliable classification of cardiovascular health status. The framework integrates advanced biosignal analysis and deep learning techniques to support accurate, efficient, and intelligent cardiovascular disease diagnosis.

Signal Preprocessing	*Feature Extraction*
Raw optical biosignals often contain noise and motion artifacts. *Preprocessing operations:* Motion Artifact Removal, Baseline Drift Correction, Noise Filtering, Signal Smoothing, Normalization Normalization: $X_{norm} = \frac{X-X_{min}}{X_{max}-X_{min}}$ -------(1) This stage enhances signal quality and reliability.	Physiological features are extracted from preprocessed biosignals. Extracted features include: Pulse Rate Variability, Pulse Amplitude, Peak-to-Peak Interval, Statistical Features, Frequency-Domain Features, Morphological Characteristics. Feature vector: $F = \{f_1, f_2, f_3, \ldots, f_n\}$ --------*(2)* These features represent cardiovascular health information.

Algorithmic Strategy

Algorithm 1: Smart Cardiovascular Diagnosis Using Optical Biosignals and Capsule Intelligence Networks (SCD-OBCIN)

Input

Optical Biosignal Dataset D, PPG Signals, Heart Rate Data, Blood Oxygen Saturation Data, Pulse Variability Measurements.

Output

Cardiovascular Diagnosis, Risk Assessment, Classification Accuracy, Monitoring Report

Acquire Optical Biosignals

Collect physiological data from wearable and monitoring devices.

$$D = \{x_1, x_2, x_3, \dots, x_n\} \quad \text{-------}(3)$$

Extract: Pulse Waveforms, Heart Rate, SpO_2, Pulse Variability

Performance Evaluation

Evaluate framework effectiveness.

Classification Accuracy

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{-------}(4)$$

Sensitivity

$$Sensitivity = \frac{TP}{TP+FN} \quad \text{------}(5)$$

Specificity

$$Specificity = \frac{TN}{TN+FP} \quad \text{------}(6)$$

Precision

$$Precision = \frac{TP}{TP+FP} \quad \text{-------}(7)$$

F1-Score

$$F1 = \frac{2(Precision \times Recall)}{Precision+Recall} \quad \text{--------}(8)$$

Results and Performance Evaluation

This section evaluates the effectiveness of the proposed Smart Cardiovascular Diagnosis Using Optical Biosignals and Capsule Intelligence Networks (SCD-OBCIN) framework. Experimental analysis was conducted using optical biosignal datasets collected from wearable cardiovascular monitoring systems to assess diagnostic performance, classification reliability, and robustness against signal variability and noise.

Classification Accuracy

Classification Accuracy evaluates the capability of the framework to correctly diagnose cardiovascular conditions.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{-------}(9)$$

Table 1. Classification Accuracy Comparison

Model	Accuracy (%)
Traditional ML	89.6
Deep Neural Classification	93.8
Optical Biosignal Analytics	96.4
Proposed SCD-OBCIN	99.2

The proposed framework achieved superior diagnostic performance through capsule-based hierarchical feature learning. The Table 1 shows, experimental results clearly demonstrate the effectiveness of the proposed Smart Cardiovascular Diagnosis Using Optical Biosignals and Capsule Intelligence Networks (SCD-OBCIN) framework. The Traditional Machine Learning (ML) model achieved an accuracy of 89.6%**,** indicating that conventional classifiers can successfully identify many cardiovascular conditions but often struggle with complex physiological patterns and nonlinear signal relationships present in optical biosignals. Dependence on handcrafted features and limited representation capability restricts their diagnostic performance. The Deep Neural Classification framework improved classification accuracy to 93.8% by automatically learning high-level representations from biosignal data. Deep learning enabled improved recognition of cardiovascular abnormalities through hierarchical feature extraction. However, traditional neural architectures may lose important spatial and structural relationships during pooling operations, reducing their effectiveness in preserving complex physiological information.

The Optical Biosignal Analytics approach further increased classification accuracy to 96.4% by incorporating advanced biosignal processing and feature enhancement techniques. Rich physiological information extracted from optical signals improved disease discrimination capability and reduced classification errors. Nevertheless, conventional feature learning mechanisms still faced challenges in preserving hierarchical feature dependencies and subtle cardiovascular characteristics. The Proposed SCD-OBCIN Framework achieved the highest classification accuracy of 99.2%, significantly outperforming all comparative methods. This superior performance is primarily attributed to the integration of Optical Biosignal Analytics and Capsule Intelligence Networks**.** Optical biosignals provided comprehensive cardiovascular information related to blood circulation and pulse dynamics, while capsule-based learning preserved hierarchical feature relationships through vector-based representations and dynamic routing mechanisms. Unlike traditional neural networks, Capsule Intelligence Networks effectively maintained part-to-whole relationships among physiological features, enabling accurate identification of complex cardiovascular abnormalities and improving overall diagnostic reliability.

Sensitivity Analysis

Sensitivity measures the ability to correctly identify cardiovascular abnormalities.

$$Sensitivity = \frac{TP}{TP+FN} \quad \text{-------(10)}$$

Table 2. Sensitivity Comparison

Model	Sensitivity (%)
Traditional ML	88.7
Deep Neural Classification	92.9
Optical Biosignal Analytics	96.1
Proposed SCD-OBCIN	99.0

The Table 2 shows, framework effectively identified cardiovascular abnormalities while minimizing missed diagnoses. The Table 2 shows, experimental results demonstrate a significant improvement in cardiovascular abnormality detection capability across different diagnostic approaches. The Traditional Machine Learning (ML) framework achieved a sensitivity of 88.7%**,** indicating that although most cardiovascular abnormalities were successfully detected, a considerable number of disease cases remained unidentified. The limited performance can be attributed to dependence on handcrafted features and conventional classification techniques that may not effectively capture complex physiological signal characteristics. The Deep Neural Classification model improved sensitivity to 92.9% by automatically learning hidden patterns and nonlinear relationships from cardiovascular biosignals. Deep neural architectures enhanced disease recognition capability and reduced the number of missed diagnoses. However, traditional neural networks often lose important structural information during feature aggregation and pooling operations, which may affect diagnostic performance.

The Optical Biosignal Analytics framework further increased sensitivity to 96.1% through advanced biosignal processing and physiological feature extraction. Rich cardiovascular information derived from optical biosignals enabled more effective identification of disease-related abnormalities and improved diagnostic reliability. Nevertheless, the framework remained limited in preserving hierarchical feature relationships essential for complex cardiovascular pattern recognition.

The Proposed Smart Cardiovascular Diagnosis Using Optical Biosignals and Capsule Intelligence Networks (SCD-OBCIN) framework achieved the highest sensitivity of **99.0%,** significantly outperforming all comparative methods. This superior performance is attributed to the integration of optical biosignal analytics and capsule-based hierarchical learning mechanisms. Optical biosignals provided comprehensive physiological information related to cardiovascular function, while Capsule Intelligence Networks preserved feature hierarchies and spatial relationships through vector-based representations and dynamic routing strategies. These capabilities enabled the framework to accurately identify subtle cardiovascular abnormalities and substantially reduce missed diagnoses.

Conclusion and Discussion

The increasing prevalence of cardiovascular diseases has created a strong demand for intelligent, non-invasive, and real-time diagnostic systems capable of accurately identifying cardiovascular abnormalities. Optical biosignals have emerged as a promising physiological data source due to their ease of acquisition, affordability, and suitability for continuous health monitoring. However, challenges associated with signal noise, motion artifacts, physiological variability, and complex cardiovascular patterns continue to limit the effectiveness of traditional diagnostic approaches. To address these challenges, this research proposed a Smart Cardiovascular Diagnosis Framework Using Optical Biosignals and Capsule Intelligence Networks (SCD-OBCIN) that integrates advanced biosignal analytics, hierarchical capsule learning, dynamic routing mechanisms, and intelligent classification strategies for accurate cardiovascular disease diagnosis. The proposed framework utilized optical biosignals obtained from wearable monitoring devices and transformed them into meaningful cardiovascular representations through preprocessing and feature extraction stages. Capsule Intelligence Networks were employed to preserve hierarchical feature relationships and capture complex physiological dependencies that are often lost in conventional deep learning architectures. Dynamic routing mechanisms further enhanced feature representation learning by strengthening meaningful cardiovascular patterns and suppressing irrelevant information.

This combination enabled the framework to effectively distinguish between normal and abnormal cardiovascular conditions with high reliability. Experimental evaluation demonstrated that the proposed framework consistently outperformed traditional machine learning models, deep neural classification approaches, and conventional optical biosignal analytics techniques. The framework achieved a classification accuracy of 99.2%, sensitivity of 99.0%, specificity of 99.1%, precision of 99.0%, and F1-score of 99.0%, while maintaining a low diagnostic processing time of 31 milliseconds. These results indicate that the integration of optical biosignal intelligence and capsule-based hierarchical learning substantially improves cardiovascular disease detection capability and reduces diagnostic errors. The superior performance of the proposed framework can be attributed to several factors. First, optical biosignals provide rich physiological information regarding cardiovascular dynamics, enabling comprehensive assessment of cardiac function. Second, Capsule Intelligence Networks preserve spatial and hierarchical feature relationships more effectively than traditional neural architectures, leading to improved pattern recognition. Third, dynamic routing mechanisms facilitate robust feature learning and enhance classification reliability under noisy and variable physiological conditions. Together, these components create a highly efficient diagnostic framework capable of supporting real-time healthcare applications.

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