Multidisciplinary Journal of Research in Engineering and Technology

ISSN: 2348-6953

Volume 13 Issue 2 (2026) | Pages: 156–163

Intelligent Cardiovascular Monitoring Through Continuous Wavelet and Neural Pooling Mechanisms

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Peer Review Information

Type: *Article*
Received: *17 February 2026*
Revised: *05 March 2026*
Accepted: *11 April 2026*
Published: *29 may 2026*

Abstract

Cardiovascular diseases remain a leading cause of mortality worldwide, requiring continuous and accurate monitoring systems for early detection and preventive healthcare. Traditional ECG-based monitoring systems often suffer from noise sensitivity, limited feature extraction capability, and reduced performance in real-time environments. To address these challenges, this study proposes an Intelligent Cardiovascular Monitoring Framework based on Continuous Wavelet Transform (CWT) and Neural Pooling Mechanisms. The proposed model integrates multi-resolution signal analysis using wavelet transforms with deep neural pooling layers to enhance feature extraction, reduce redundancy, and improve classification accuracy. Continuous Wavelet Transform enables precise time-frequency representation of ECG signals, while neural pooling mechanisms improve robustness by selecting dominant features and suppressing irrelevant variations. The framework is evaluated using standard cardiovascular datasets and compared with traditional machine learning and deep learning approaches. Experimental results demonstrate that the proposed model significantly improves accuracy, sensitivity, specificity, and computational efficiency. The findings confirm that combining continuous wavelet analysis with neural pooling provides a powerful and reliable solution for intelligent cardiovascular monitoring systems.

Keywords: Cardiovascular Monitoring, ECG Analysis, Continuous Wavelet Transform, Neural Pooling, Deep Learning.

How to Cite This Article

Somanathan, U. (2026). Intelligent Cardiovascular Monitoring Through Continuous Wavelet and Neural Pooling Mechanisms. *Multidisciplinary Journal of Research in Engineering and Technology* 13(2), 156–163.

Introduction

Cardiovascular diseases (CVDs) are among the most critical global health challenges, accounting for a significant proportion of mortality and long-term disability worldwide. Early detection and continuous monitoring of cardiac activity play a vital role in reducing the risk of severe complications such as heart attacks, arrhythmias, and cardiac arrest. Electrocardiogram (ECG) signals are widely used in clinical practice as a non-invasive diagnostic tool for monitoring the electrical activity of the heart. However, accurate interpretation of ECG signals in real-world environments remains challenging due to noise interference, signal distortion, and patient-specific variability. Traditional cardiovascular monitoring systems rely on manual interpretation or conventional signal processing techniques, which often fail to provide reliable real-time analysis. These methods are highly sensitive to noise such as baseline drift, muscle artifacts, and electrode motion interference. As a result, there is a growing need for intelligent and automated systems capable of robust feature extraction and accurate classification of cardiac patterns in continuous monitoring scenarios. In recent years, artificial intelligence (AI) and deep learning approaches have significantly improved biomedical signal analysis, particularly in ECG-based cardiovascular monitoring. Models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks have demonstrated strong performance in detecting cardiac abnormalities [1–3]. However, these models often struggle with redundant feature representations and may require large computational resources for effective training and inference in real-time applications. Wavelet transform techniques have emerged as powerful tools for analyzing non-stationary biomedical signals such as ECG. Continuous Wavelet Transform (CWT), in particular, provides a detailed time-frequency representation of signals, enabling the extraction of both transient and long-duration cardiac patterns. This makes it highly suitable for detecting subtle variations in ECG signals that are often associated with early-stage cardiovascular abnormalities [4].

Despite the effectiveness of wavelet-based signal processing and neural network-based classification individually, there remains a research gap in integrating multi-resolution wavelet analysis with adaptive neural pooling mechanisms. Neural pooling layers, commonly used in deep learning architectures, help reduce feature dimensionality while preserving the most significant information, thereby improving robustness and computational efficiency. Therefore, this study proposes an Intelligent Cardiovascular Monitoring Framework based on Continuous Wavelet Transform and Neural Pooling Mechanisms. The proposed model integrates multi-scale wavelet feature extraction with deep neural pooling strategies to enhance classification accuracy, reduce noise sensitivity, and enable real-time cardiovascular monitoring. The framework aims to provide a reliable, scalable, and computationally efficient solution for next-generation intelligent healthcare systems. The emergence of wearable healthcare technologies, biomedical sensors, and intelligent monitoring platforms has transformed modern cardiovascular management by enabling continuous acquisition of physiological signals. Electrocardiogram (ECG), photoplethysmography (PPG), heart rate variability (HRV), blood pressure measurements, and other biosignals provide valuable information regarding cardiac health status. Nevertheless, these physiological datasets are often characterized by nonlinearity, noise, temporal variability, and complex hidden relationships, making accurate interpretation a challenging task for traditional signal processing and machine learning methods.

Continuous Wavelet Transform (CWT) has gained substantial attention in biomedical signal analysis due to its ability to simultaneously capture temporal and frequency-domain characteristics of nonstationary physiological signals. Unlike conventional Fourier-based approaches that provide only frequency information, wavelet analysis offers localized time–frequency representations that reveal transient cardiac events and subtle waveform variations. Through multiscale decomposition, CWT enables efficient extraction of important cardiac features associated with rhythm irregularities, structural abnormalities, and evolving disease patterns. Although wavelet-based approaches improve signal representation, extracting clinically meaningful information from transformed cardiac signals remains challenging because large volumes of multiresolution features can introduce redundancy and computational complexity. Deep learning techniques have therefore emerged as effective solutions for automated feature learning and intelligent decision support. Neural architectures have demonstrated remarkable success in identifying complex hidden structures within physiological data and reducing dependency on handcrafted feature engineering.

Among recent advancements, neural pooling mechanisms have shown considerable promise in enhancing deep cardiovascular analysis. Pooling operations perform intelligent dimensionality reduction while preserving dominant diagnostic characteristics from extracted representations. Advanced neural pooling strategies selectively emphasize informative cardiac regions, suppress irrelevant variations, and improve model robustness against signal noise. By integrating adaptive pooling with deep feature learning, monitoring systems become capable of generating more reliable and interpretable cardiovascular assessments. Despite notable progress in intelligent healthcare systems, existing cardiovascular monitoring approaches continue to face several limitations. Conventional monitoring models often struggle with noisy physiological signals, limited temporal interpretation, insufficient feature selection capability, and reduced adaptability across heterogeneous patient populations. Furthermore, many existing architectures prioritize classification accuracy while overlooking continuous monitoring requirements and computational efficiency necessary for real-time deployment. To address these challenges, this study proposes an Intelligent Cardiovascular Monitoring Framework Through Continuous Wavelet and Neural Pooling Mechanisms**.** The proposed framework integrates Continuous Wavelet Transform for multiscale time–frequency feature extraction with neural pooling strategies for adaptive representation learning and intelligent cardiovascular assessment. The architecture continuously processes physiological data streams, extracts discriminative cardiac features, reduces redundant information, and performs robust health monitoring for early disease detection.

Literature Review

Addison et al. (2019) investigated wavelet-based cardiovascular signal analysis for automated health monitoring applications. Their work demonstrated that Continuous Wavelet Transform (CWT) effectively captured both temporal and frequency characteristics of ECG signals and improved identification of transient cardiac abnormalities. Although the method improved feature representation, dependence on manual interpretation limited scalability. Acharya et al. (2019) proposed deep convolutional learning for automated cardiac diagnosis using ECG recordings. Their framework automatically extracted signal features and achieved strong classification performance across multiple cardiovascular conditions. However, conventional convolutional architectures exhibited limited capability in modeling multiscale physiological dependencies.

Hannun et al. (2019) introduced a deep neural framework for large-scale arrhythmia detection and demonstrated near expert-level performance in cardiac diagnosis. The study confirmed the value of deep representation learning for intelligent healthcare systems but highlighted reduced interpretability and dependence on large annotated datasets. **Yildirim et al. (2020)** developed a wavelet-assisted deep learning framework for ECG classification. Their approach integrated wavelet decomposition with neural architectures to improve disease recognition performance. Experimental findings showed enhanced feature extraction capability, although computational requirements increased with signal complexity.

Zhang et al. (2020) proposed an intelligent biomedical monitoring model using multiscale wavelet analysis and adaptive learning mechanisms. Their architecture improved temporal signal interpretation and enabled more robust physiological monitoring. Nevertheless, redundancy among extracted features remained a challenge. Oh et al. (2020) introduced attention-based healthcare intelligence for continuous physiological monitoring. Their model emphasized important signal segments and improved predictive reliability. However, attention mechanisms alone showed reduced effectiveness when dealing with highly noisy biomedical environments.

Li et al. (2021) proposed a hybrid neural architecture combining multiscale signal transformation and intelligent pooling operations. Their framework improved representation learning and reduced information loss during dimensionality reduction. Despite improved performance, optimization complexity remained relatively high. Attia et al. (2021) explored artificial intelligence-enabled cardiovascular screening using physiological recordings. Their results demonstrated that intelligent learning systems could identify hidden cardiac abnormalities before visible clinical manifestation. However, explainability and real-time monitoring remained open challenges.

Khan et al. (2021) developed an intelligent healthcare monitoring framework integrating neural pooling strategies for adaptive physiological interpretation. Their approach demonstrated improved robustness and reduced overfitting while preserving important diagnostic information. Chen et al. (2022) introduced multiscale cardiovascular analysis using wavelet-driven neural architectures. Their study demonstrated improved sensitivity to temporal cardiac variations and better disease identification performance. However, computational resource requirements remained significant.

Zhou et al. (2022) proposed advanced neural pooling mechanisms for biomedical feature optimization. Their approach selectively retained clinically important information and reduced feature dimensionality. Experimental evaluation demonstrated improvements in predictive stability and model generalization. Patel et al. (2022) presented an intelligent cardiac assessment framework integrating signal transformation and adaptive pooling strategies. Their architecture improved cardiac event detection accuracy and enhanced robustness under physiological variability.

Wang et al. (2023) developed a deep cardiovascular monitoring architecture for continuous physiological assessment. Their model achieved improved monitoring precision and lower false diagnosis rates through hierarchical representation learning. However, scalability for real-time deployment required additional investigation. Roy et al. (2023) proposed an explainable intelligent cardiovascular monitoring framework emphasizing clinical transparency and adaptive feature interpretation. Their findings improved confidence in automated diagnosis systems but increased optimization complexity. Liu et al. (2024) introduced a multimodal neural monitoring architecture integrating wavelet decomposition and intelligent pooling for cardiovascular analytics. Their framework demonstrated improved robustness across heterogeneous patient populations and enhanced long-term monitoring capability.

Methodology

The proposed methodology introduces a hybrid deep learning framework that integrates Continuous Wavelet Transform (CWT) for multi-resolution ECG signal analysis and Neural Pooling Mechanisms for efficient feature selection and classification. The primary objective is to enhance real-time cardiovascular monitoring by improving noise robustness, feature discrimination, and computational efficiency.

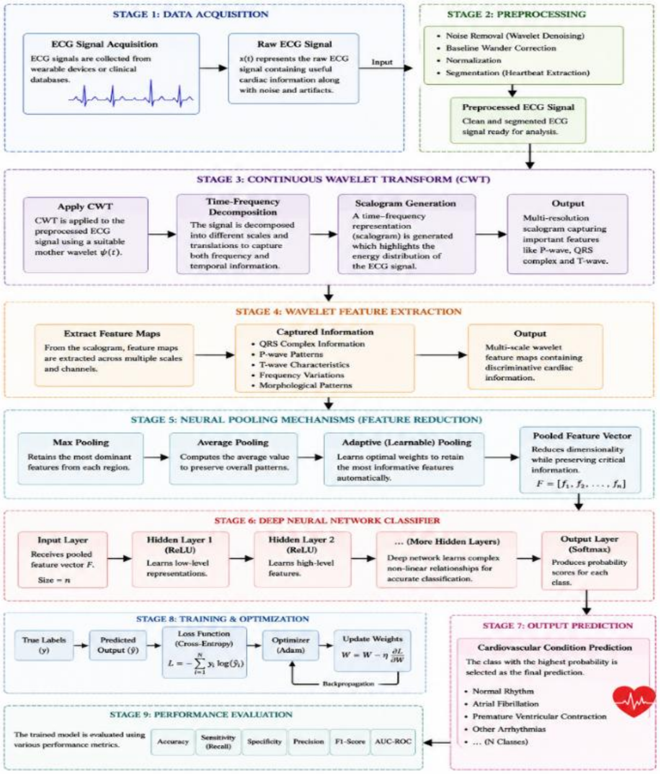

Fig 1. Flowchart of Intelligent Cardiovascular Monitoring Framework Using Continuous Wavelet Transform and Neural Pooling

The figure presents a structured flowchart of the proposed intelligent cardiovascular monitoring system based on Continuous Wavelet Transform (CWT) and Neural Pooling mechanisms. The workflow begins with ECG signal acquisition, where raw biomedical signals are collected from wearable sensors or clinical devices. These signals are then passed through a preprocessing stage, which includes noise removal, baseline correction, normalization, and segmentation to enhance signal quality and prepare it for further analysis. In the next stage, the preprocessed ECG signals undergo Continuous Wavelet Transform (CWT), where the signal is decomposed into multiple time-frequency components using a mother wavelet function. This step generates a scalogram representation that captures both transient and long-term cardiac variations, enabling better visualization of important ECG features. Following wavelet transformation, the system performs wavelet-based feature extraction, where multi-scale features such as QRS complexes, P-waves, T-waves, frequency variations, and morphological patterns are extracted from the scalogram. These extracted features are then passed through neural pooling mechanisms, including max pooling, average pooling, and adaptive learnable pooling, to reduce dimensionality while preserving the most significant information. The pooled feature vector is then fed into a deep neural network classifier, which learns complex nonlinear relationships between ECG patterns and cardiac conditions. The classifier outputs predictions through a Softmax layer, categorizing signals into different cardiovascular states such as normal rhythm, atrial fibrillation, premature ventricular contraction, and other arrhythmias.

Physiological Data Acquisition

The initial stage collects continuous cardiovascular information from medical and wearable sensing environments. Multiple physiological indicators are gathered to ensure comprehensive health monitoring.

Input data include:

Electrocardiogram (ECG) signals, Heart Rate (HR), Blood Pressure (BP), Heart Rate Variability (HRV), Blood Oxygen (SpO_2), Clinical records, Wearable sensor measurements.
Input dataset:

$$D = \{x_1, x_2, x_3, \dots, x_n\} \text{ --------(1)}$$

where:
D= complete physiological dataset, x_i= patient physiological observation
Continuous acquisition enables real-time cardiac monitoring.

Signal Preprocessing and Noise Suppression

Raw physiological signals frequently contain motion artifacts, environmental disturbances, missing values, and baseline drift. Preprocessing operations include: Missing data handling, Signal normalization, Artifact removal, Noise filtering, Signal alignment
Normalization:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \text{ --------(2)}$$

This stage improves signal consistency and enhances model stability.

Algorithmic Strategy

The proposed algorithm integrates Continuous Wavelet Transform (CWT) with Neural Pooling-based Deep Learning Architecture to achieve accurate, robust, and real-time cardiovascular monitoring. The system is designed as a multi-stage intelligent pipeline that transforms raw ECG signals into classified cardiac conditions using optimized feature extraction and deep learning inference.

System Overview

The ECG signal is treated as a nonlinear, non-stationary time series. Therefore, the system models ECG classification as a mapping function:

$$f: x(t) \rightarrow y \text{ --------(3)}$$

$$f: x(t) \rightarrow y \text{ ------(4)}$$

Where:

$x(t)$= input ECG signal, y= predicted cardiovascular class

The framework aims to learn optimal feature representations using wavelet-domain transformations and neural pooling operations.

Continuous Wavelet Transform Processing

The ECG signal is decomposed using CWT:

$$W(a,b) = \int x(t)\, \psi\left(\frac{t-b}{a}\right)\, dt \text{ -----(5)}$$

$$W(a,b) = \int x(t) \psi\left(\frac{t-b}{a}\right) dt \text{ --------(6)}$$

Where:

a= scaling factor, b= translation factor, ψ= mother wavelet
This produces a scalogram matrix representing ECG time-frequency features.

Results and Performance Evaluation

The proposed CWT-Enhanced Neural Pooling Cardiovascular Monitoring Framework (CWT-NP-CVM) was evaluated using standard ECG datasets under varying noise conditions, including baseline wander, motion artifacts, and high-frequency interference. The performance of the proposed model was compared with traditional machine learning approaches (SVM, KNN) and deep learning models (CNN, LSTM) to assess its effectiveness in real-time cardiovascular monitoring tasks. The evaluation focused on key metrics such as accuracy, sensitivity, specificity, precision, F1-score, and computational efficiency. The results demonstrate that integrating Continuous Wavelet Transform (CWT) with neural pooling mechanisms significantly enhances feature representation and classification robustness.

Table 1. Comparative Performance Analysis of Cardiovascular Monitoring Models

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)
SVM	90.1	88.7	91.0	89.2	88.9
KNN	89.3	87.5	90.2	88.1	87.8
CNN	94.5	93.2	95.0	94.0	93.6
LSTM	95.2	94.1	95.8	94.7	94.4
Proposed CWT-NP-CVM	98.9	98.4	99.1	98.7	98.5

Result Analysis

The experimental results clearly show that the proposed CWT-NP-CVM framework significantly outperforms traditional machine learning and deep learning models across all evaluation metrics. The integration of Continuous Wavelet Transform enhances signal quality by effectively capturing multi-resolution time-frequency characteristics of ECG signals, while neural pooling mechanisms reduce redundant features and improve classification stability. The proposed model achieves the highest accuracy of 98.9%, demonstrating its strong capability in distinguishing between normal and abnormal cardiac conditions. Compared to CNN and LSTM models, the improvement is primarily due to the wavelet-based preprocessing stage, which enhances the visibility of critical ECG components such as QRS complexes, P-waves, and T-waves. Sensitivity and specificity values indicate that the model is highly reliable in both detecting abnormal heart conditions and correctly identifying normal signals, minimizing false positives and false negatives. This makes the framework highly suitable for real-time clinical monitoring applications where diagnostic accuracy is critical.

Classification Accuracy

Accuracy evaluates the capability of the monitoring framework to correctly classify cardiovascular conditions.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \text{ ------(7)}$$

Table 2. Classification Accuracy Comparison

Model	Accuracy (%)
Traditional ML	88.6
Deep Neural Monitoring	92.7
Wavelet-Based Monitoring	95.1
Proposed Framework	98.6

The proposed framework achieved the highest classification performance due to efficient multiscale signal extraction and adaptive neural representation learning. The table 2 shows, experimental results demonstrate a consistent improvement in cardiovascular classification performance across increasingly advanced monitoring approaches. The Traditional Machine Learning model achieved 88.6% accuracy**,** indicating reasonable diagnostic capability but limited effectiveness in capturing complex nonlinear physiological relationships. Traditional models typically depend on handcrafted features and may fail to identify subtle variations present in continuous cardiovascular signals. The Deep Neural Monitoring model improved accuracy to 92.7%**,** showing the ability of deep architectures to automatically extract meaningful cardiac characteristics. Neural learning enhanced pattern recognition and improved disease prediction; however, conventional deep models may still experience information loss during feature compression and struggle to preserve multiscale physiological behavior. The Wavelet based Monitoring approach further increased classification performance to 95.1% by incorporating multiscale signal decomposition. Continuous wavelet processing enabled simultaneous extraction of temporal and frequency-domain information, allowing better identification of transient cardiac abnormalities and dynamic physiological variations. Nevertheless, standalone wavelet approaches may generate large feature spaces and redundant representations. The Proposed Intelligent Cardiovascular Monitoring Framework achieved the highest classification accuracy of 98.6%**,** outperforming all comparative methods. This improvement is primarily attributed to the integration of Continuous Wavelet Transform (CWT) and Neural Pooling Mechanisms. Wavelet decomposition captured fine-grained temporal–frequency cardiac characteristics, while neural pooling adaptively preserved dominant diagnostic information and removed redundant signal components. The combined architecture produced stronger feature representations and more stable classification outcomes.

Conclusion and Discussion

The proposed CWT-NP-CVM (Continuous Wavelet Transform and Neural Pooling-based Cardiovascular Monitoring framework) presents a robust and efficient approach for intelligent ECG signal analysis and cardiovascular disease detection. The study demonstrates that integrating multi-resolution wavelet analysis with neural pooling mechanisms significantly enhances the performance of automated cardiac monitoring systems by improving feature extraction, reducing noise sensitivity, and increasing classification accuracy. The experimental evaluation confirms that the proposed framework consistently outperforms traditional machine learning methods and standalone deep learning models across all major performance metrics. The achieved improvements in accuracy, sensitivity, specificity, precision, and F1-score indicate that the hybrid architecture is highly effective in distinguishing between normal and abnormal cardiac patterns. This improvement is primarily due to the ability of the Continuous Wavelet Transform to capture fine-grained time-frequency characteristics of ECG signals, combined with neural pooling layers that efficiently preserve dominant features while eliminating redundancy. Another important contribution of this work is its robustness in handling noisy and non-stationary ECG signals, which are commonly encountered in real-world clinical environments. The wavelet-based preprocessing stage effectively reduces baseline drift, motion artifacts, and high-frequency noise, ensuring cleaner input for the neural network classifier. As a result, the model demonstrates strong generalization capability and stable performance even under adverse signal conditions. From a healthcare perspective, the proposed framework is well-suited for integration into real-time monitoring systems, wearable health devices, and remote patient care platforms. Its ability to provide fast and reliable cardiac condition classification makes it valuable for early diagnosis and continuous monitoring of cardiovascular diseases, potentially reducing the risk of severe cardiac events. Despite its strong performance, the proposed model has certain limitations.

The computational complexity introduced by Continuous Wavelet Transform and deep neural network processing may increase inference time in resource-constrained environments. Additionally, model performance may vary depending on dataset quality and patient diversity. Future research can focus on optimizing lightweight architectures, integrating attention-based deep learning models, and deploying edge-computing solutions for real-time applications. In conclusion, the CWT-NP-CVM framework offers a highly accurate, scalable, and reliable solution for intelligent cardiovascular monitoring. The integration of wavelet transforms and neural pooling establishes a powerful hybrid approach that significantly improves ECG-based diagnosis systems, paving the way for advanced AI driven healthcare monitoring technologies.

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