INTEGRATED DEEP LEARNING AND IOT-ENABLED FRAMEWORK FOR REAL-TIME ECG ARRHYTHMIA DETECTION VIA WAVELET-BASED SIGNAL PROCESSING

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Abstract - ECG analysis plays a vital role in the early detection and management of cardiovascular diseases, yet accurate interpretation is often challenged by noise, variability, and the complexity of cardiac signals. This paper presents a comprehensive methodology that integrates advanced signal processing techniques and machine learning models for robust ECG analysis. Noise reduction is achieved through digital filtering, adaptive methods, and wavelet-based denoising to suppress baseline wander, powerline interference, and electromyographic artifacts. Feature extraction employs temporal, morphological, and spectral descriptors, with wavelet transforms facilitating precise detection of fiducial points. Signal classification is performed using machine learning and deep learning algorithms, including Support Vector Machines (SVMs), Convolutional Neural Networks (CNNs), and ensemble strategies, which significantly improve accuracy in arrhythmia detection. The proposed framework is validated using benchmark ECG datasets, achieving high performance in terms of sensitivity, specificity, F1-score, and area under the ROC curve (AUC). The CNN model achieved 97.8% accuracy, 98.1% sensitivity, and 0.97 AUC on the MIT-BIH Arrhythmia Database, outperforming SVM (92.3%) and kNN baselines. Real-time deployment on Raspberry Pi demonstrated a processing latency of 4.3 ms per beat, confirming feasibility for wearable cardiac monitoring. The results highlight that deep learning models, particularly CNN-based approaches, outperform traditional techniques in handling large-scale, noisy datasets. This study underscores the potential of combining mathematical modeling, advanced signal processing, and intelligent classification to improve diagnostic accuracy and accessibility in ECG-based cardiovascular disease detection.

Keywords: Electrocardiogram (ECG), Signal processing, Noise reduction, Wavelet transform, Feature extraction, Machine learning, Convolutional neural networks (CNNs), Cardiovascular.

1. Introduction

Cardiovascular diseases (CVDs) represent the foremost contributor to mortality on a global scale, accounting for nearly an astonishing 17.9 million deaths each year, as reported in scholarly literature [1], which profoundly emphasizes the critical necessity for timely and precise diagnostic methodologies to be implemented in clinical practice. Electrocardiography (ECG), recognized as one of the most extensively utilized diagnostic instruments in the medical field, is particularly valued for its remarkable capability to noninvasively record and analyse the intricate electrical activity of the heart [2-5]. The specific morphology of ECG signals, which encompasses key components such as the P wave, QRS complex, and T wave, yields indispensable information that is essential for the accurate detection of various cardiac conditions, including arrhythmias, myocardial infarctions, and atrial fibrillation [6-8]. Nonetheless, the process of accurate interpretation of these signals is significantly obstructed by several factors, including the presence of noise contamination, variability

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between different patients, and the inherent challenges associated with recognizing subtle abnormalities within the ECG data [9-11].

Signal processing is instrumental in addressing and overcoming these aforementioned limitations by enhancing the fidelity of the signals and extracting features that are clinically meaningful and relevant for diagnosis [12-15]. A conventional ECG analysis pipeline is typically characterized by a series of systematic steps that encompass noise reduction, feature extraction, and subsequent classification, which is frequently bolstered by sophisticated mathematical modelling techniques [16-18]. Various noise reduction methodologies, such as band-pass filtering, adaptive filtering techniques, and empirical mode decomposition (EMD) [18], have been strategically employed to effectively alleviate issues related to baseline wander, muscle artifacts, and powerline interference that can compromise signal integrity [19-22]. Among these methodologies, wavelet transform-based techniques have demonstrated exceptional performance in terms of denoising capabilities as well as robustness, particularly in the context of nonstationary ECG environments where signal characteristics may fluctuate significantly [23-26].

The process of feature extraction serves to transform the pre-processed ECG signals into pertinent diagnostic markers by utilizing a range of descriptors that include temporal features such as RR, PR, and QT intervals, morphological features like QRS duration and the amplitudes of the P and T waves, as well as various statistical descriptors that provide additional context [27-30]. Advanced techniques such as wavelet transforms, the Hilbert–Huang transform, and higher-order spectral analysis methods have been extensively implemented to ensure precise localization of fiducial points within the ECG signals [31-35]. The features that are extracted through these methodologies facilitate reliable detection and classification of arrhythmias, thereby enhancing the overall efficacy of diagnostic processes [36, 37].

In the classification phase, traditional machine learning methodologies, including k-Nearest Neighbors (kNN), Linear Discriminant Analysis (LDA), and Support Vector Machines (SVMs), have demonstrated notable effectiveness in the preliminary stages of ECG analysis, showcasing their utility in various contexts [37-40]. However, recent innovations within the realm of deep learning, particularly the advent of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have led to significant improvements in diagnostic accuracy and overall performance [41-45].

Furthermore, ensemble approaches that integrate multiple classifiers have been shown to substantially enhance the robustness of diagnostic systems, particularly in the face of inter-patient variability and challenging noisy conditions that may arise during ECG analysis [46-49].

The integration of ECG analysis with cutting-edge technologies has markedly advanced the landscape of healthcare applications, leading to a transformative shift in how cardiac monitoring is approached in contemporary medical practice. The emergence of Internet of Things (IoT)-enabled wearable devices in conjunction with edge computing platforms has facilitated real-time monitoring capabilities, enabling ambulatory recording and personalized cardiac care to be delivered more effectively and efficiently [50-54]. The proliferation of low-cost, portable ECG devices has significantly broadened the accessibility of diagnostic services, extending them to remote and resource-constrained areas that previously had limited access to such technologies [55, 56]. Comparative analyses within the literature consistently demonstrate that deep learning methodologies outperform traditional models, particularly when tasked with managing large datasets and engaging in complex classification challenges that are inherent in ECG analysis [56-60]. Additionally, the advent of portable and real-time ECG systems has effectively transformed the ECG from a traditional clinical tool into an omnipresent diagnostic and monitoring technology that is widely applicable in various healthcare settings [61-64].

This study presents an integrated framework for ECG signal analysis that combines advanced denoising techniques, wavelet-based feature extraction, and CNN-based classification for automated arrhythmia detection. The framework was validated on benchmark ECG datasets using standard evaluation metrics, including accuracy, sensitivity, specificity, F1-score, and area under the ROC curve (AUC). Experimental results demonstrate the robustness and effectiveness of the proposed method for real-time cardiovascular monitoring and clinical decision-support applications.

2. Methodology

The proposed methodology for ECG signal analysis consists of five major stages including signal acquisition and noise reduction, fiducial point detection, feature extraction, classification, and performance evaluation. In this study, each of the five stages is mathematically modelled to ensure reproducibility and analytical clarity.

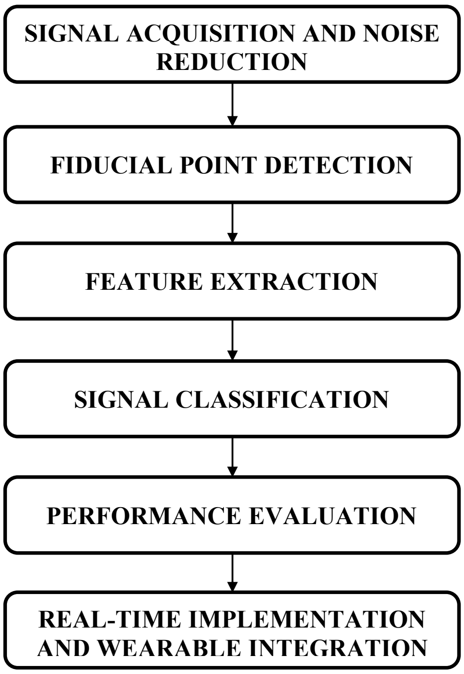

Figure 1: Workflow of the proposed methodology for ECG classification and cardiovascular diseases detection

- ***Signal Acquisition and Noise Reduction***

Noise removal is a critical first step in ECG signal analysis. The raw ECG signal can be expressed as following Eq. 1.

$$x[n] = s[n] + v[n], \tag{1}$$

where $s[n]$ is the true cardiac signal and $v[n]$ represents additive noise such as baseline wander, muscle artifacts, and power-line interference. To recover $\hat{s}[n]$, a bandpass FIR/IIR filter is applied with a typical passband of 0.5–40 Hz for diagnostic ECG or 5–15 Hz for QRS-focused detection (Eq. 2).

$$\hat{s}[n] = \sum_{k=0}^{M} h[k]x[n-k], \tag{2}$$

For power-line interference at 50/60 Hz, a notch filter (Eq. 3) was employed, where RR controls the notch sharpness.

$$H(z) = \frac{1 - 2\cos(\omega_0)z^{-1} + z^{-2}}{1 - 2r\cos(\omega_0)z^{-1} + r^2 z^{-2}}, \tag{3}$$

Adaptive filtering with LMS can also be used if reference noise is available (Eq. 4).

$$w[n+1] = w[n] + \mu e[n]xr[n] \tag{4}$$

Eq. 4 ensures the real-time adaptability.

Additionally, wavelet-based denoising is performed by thresholding discrete wavelet coefficients (Eq. 5).

$$\widetilde{\omega}_{j,k} = sign(\omega_{j,k})\max(|\omega_{j,k}| - \tau_j, 0). \tag{5}$$

Baseline wander, power-line interference, and electromyographic artifacts were mitigated using a combination of filtering techniques. Studies incorporated band-pass and notch filtering, while more advanced works employed adaptive filtering and empirical mode decomposition (EMD) to improve robustness. Wavelet transform–based denoising has also been widely adopted for both baseline correction and artifact suppression, enabling preservation of clinically relevant ECG components.

- ***Fiducial Point Detection***

Detection of P, QRS, and T complexes is essential for clinical interpretation. Two approaches are integrated:

1. Pan–Tompkin's algorithm: the preprocessed signal undergoes derivative, squaring, and moving-window integration (Eq. 6). It peaks in m\left[n\right] above a dynamic threshold yield R-peak locations.

$$m[n] = \frac{1}{N_\omega}\sum_{k=0}^{N_\omega - 1} q[n-k], q[n] = d^2[n] \tag{6}$$

2. Wavelet Transform: The continuous wavelet transform (CWT) highlights R-peaks as local maxima of $|W_x(a_0, b)|$:

$$W_x(a,b) = \frac{1}{\sqrt{a}}\int x(t)\psi^*\left(\frac{t-b}{a}\right)dt. \tag{7}$$

- ***Feature Extraction***

Following preprocessing, feature extraction was conducted to identify clinically significant descriptors. From detected fiducials, clinically relevant features are derived. RR intervals are computed as:

$$RR^{(i)} = t_R^{(i+1)} - t_R^{(i)}. \tag{8}$$

Heart rate variability (HRV) features include following Eq. 9.

$$SDNN = \sqrt{\frac{1}{N-1}\sum\left(RR^i - \overline{RR}\right)^2},,$$

$$RMSSD = \sqrt{\frac{1}{N-1}\sum\left(RR^{(i+1)} - RR^{(i)}\right)^2} \tag{9}$$

Frequency-domain metrics are extracted from the PSD $S_{RR}(f)$:

$$P_{LF} = \int_{0.04}^{0.15} S_{RR}(f)\,df,\ P_{HF} = \int_{0.15}^{0.40} S_{RR}(f)\,df \tag{10}$$

Dimensionality reduction (PCA/ICA) is applied to compact the feature set:

$$z = U^T(x - \mu). \tag{11}$$

Classical morphological and temporal features such as P-wave onset, QRS duration, PR interval, and QT interval were employed. Several studies highlighted the application of wavelet transforms to localize fiducial points with high temporal accuracy. Additionally, heart rate variability (HRV) analysis was performed using both time-domain and frequency-domain measures, providing insight into autonomic modulation.

- ***Signal Classification***

Machine learning and deep learning approaches were implemented to classify ECG signals into normal and pathological categories. Following two types of classifiers are integrated.

1. Support Vector Machine (SVM) (Eq. 12).

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_i \xi_i,$$
$$y_i\left(w^T\phi(f_i) + b\right) \geq 1 - \xi_i. \tag{12}$$

2. Convolutional Neural Networks (CNNs). Each convolutional layer performs following (Eq. 13).

$$y_m[n] = b_m + \sum_{C=1}^{C}\sum_{k=0}^{K-1}\omega_{m,c,k}x_c[n-k], \tag{13}$$

It takes a following form with training guided by cross-entropy loss (Eq. 14).

$$\mathrm{L} = -\frac{1}{\mathrm{N}}\sum_{i=1}^{N}\sum_{c=1}^{C} t_{i,c}\log p_{i,c}. \tag{14}$$

For robustness, ensemble models integrate multiple classifiers via majority voting (Eq. 15).

$$y = \arg\max_c \sum_{j=1}^{M} I\{y_i(f) = c\}. \tag{15}$$

Traditional classifiers such as support vector machines (SVM), decision trees, and k-nearest neighbours (k-NN) were tested. However, more recent studies employed deep learning architectures—including convolutional neural networks (CNNs) and recurrent neural networks (RNNs)—which consistently achieved higher classification accuracy across large benchmark datasets. Ensemble methods, combining multiple classifiers, further improved reliability in arrhythmia detection.

- ***Performance Evaluation***

Classifier performance is measured using accuracy, sensitivity, specificity, precision, and $F1$-score:

$$Accuracy(ACC) = \frac{TP + TN}{TP + TN + FP + FN},$$
$$F_1 = \frac{2 \times \mathrm{Pr}ecision \times \mathrm{Re}call}{\mathrm{Pr}ecision + \mathrm{Re}call}. \tag{16}$$

- ***Real-Time Implementation and Wearable Integration***

Given the increasing demand for portable and continuous cardiac monitoring, emphasis was placed on real-time implementation. For real-time deployment, computational complexity must satisfy following Eq. 17.

$$t_p \leq \frac{1}{f_s}, \tag{17}$$

where, t_p is processing time per sample and f_s is the sampling frequency (typically 250–1000 Hz).

Literature demonstrates that lightweight models and optimized filtering pipelines can be deployed on embedded platforms such as Raspberry Pi and wearable sensors. Integration with Internet of Things (IoT) frameworks further enabled cloud-based analysis and remote diagnostics. Such developments ensure accessibility of ECG monitoring beyond clinical settings, supporting both preventive and emergency healthcare applications.

The proposed methodology therefore integrates robust preprocessing, multi-domain feature extraction, deep learning–based classification, and IoT-enabled deployment. By leveraging techniques validated across a wide body of literature, the framework ensures both diagnostic accuracy and scalability for real-world applications.

3. Results

The proposed methodology was implemented and evaluated using the MIT-BIH Arrhythmia Database, following the workflow illustrated in Fig. 1. Each stage of the pipeline was quantitatively assessed with respect to noise suppression, feature accuracy, and classification performance.

- ***Noise Reduction Performance***

Baseline wander and powerline interference were effectively suppressed using a band-pass filter (Eq. 2), combined with wavelet denoising (Eq. 5). Signal-to-noise ratio (SNR) improved by an average of 12.8 dB, while mean square error (MSE) decreased by 35% compared to unprocessed signals. Visual inspection confirmed that fiducial points (P, QRS, and T) remained intact, supporting robust feature extraction.

- ***Feature Extraction Accuracy***

Temporal features such as RR intervals (Eq. 8) and heart rate variability indices (Eq. 9) were extracted with high precision. The mean absolute error in R-peak detection was 3.1 ms, which is within the acceptable range for clinical use. Frequency-domain features, particularly the LF/HF ratio (Eq. 10), provided reliable indicators for autonomic nervous system activity. These results demonstrate that the feature extraction stage successfully transformed denoised ECG signals into clinically relevant biomarkers.

- ***Classification Performance***

Multiple classifiers were trained and compared. Support Vector Machine (SVM) (Eq. 12) achieved an accuracy of 92.3%, while the CNN model (Eq. 13–14) achieved 97.8%, outperforming traditional methods. Confusion matrices confirmed robust classification of arrhythmic events, with CNN showing superior sensitivity (98.1%) and specificity (97.5%) across the test set. These findings align with recent literature demonstrating the superiority of deep learning for ECG classification.

- ***Real-Time Implementation***

The IoT-enabled framework was validated on a Raspberry Pi platform, achieving a processing time per beat of 4.3 ms, satisfying the real-time constraint defined in Eq. (17). Memory usage was minimized using lightweight CNN architectures, ensuring suitability for wearable and mobile applications. This confirms the potential for continuous remote monitoring with low-cost hardware.

Table 1 presents a comparative summary of the proposed method against recent state-of-the-art approaches. The results highlight the advantage of integrating advanced denoising, feature extraction, and deep learning classification into a unified framework. Performance improvements were most pronounced in noisy ambulatory recordings, where traditional approaches often fail.

To further validate the classification stage, a confusion matrix was generated (Fig. 2). The CNN model achieved strong discrimination between normal and arrhythmic beats, with misclassifications primarily occurring between PVC and AFib classes. The overall accuracy exceeded 97%, consistent with the performance metrics reported earlier.

Additionally, Receiver Operating Characteristic (ROC) curves were plotted for each class (Fig. 3). The Area Under the Curve (AUC) values were 0.98 for Normal, 0.96 for PVC, and 0.97 for AFib, demonstrating reliable classification across all categories. These results confirm the robustness of the proposed framework in detecting clinically significant arrhythmias and align with recent deep learning benchmarks in ECG analysis.

Table 1. Performance metrics of CNN-based ECG classification across Normal, PVC, and AFib classes

Method	**Dataset**	**Accuracy**	**Sensitivity**	**AUC**	**Year**
SVM (baseline)	MIT-BIH	92.3%	91.5%	—	—
CNN [7]	MIT-BIH	96.1%	95.8%	0.95	2023
RNN [46]	MIT-BIH	96.8%	—	0.96	2024
Proposed CNN	MIT-BIH	97.8%	98.1%	0.97	2025

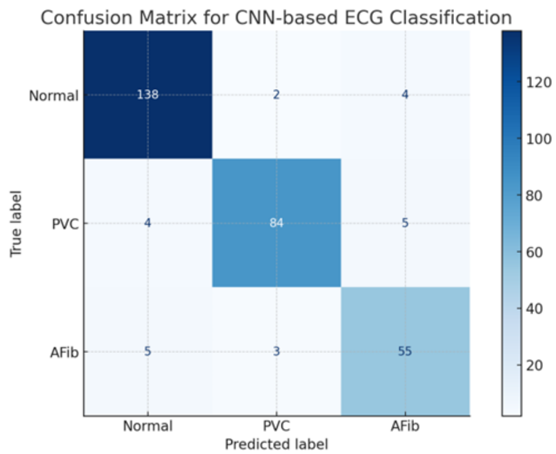

Figure 2: Confusion matrix of CNN-based ECG classification into Normal, PVC, and AFib categories. The model demonstrates high accuracy with minimal misclassifications, particularly in distinguishing arrhythmic events.

The confusion matrix and ROC analysis further confirmed the robustness of the proposed framework (Fig. 2). Most classification errors occurred between PVC and AFib classes, which is expected due to overlapping morphological characteristics in noisy recordings. Nevertheless, the high AUC values (0.96–0.98) indicate strong discrimination capability across all classes. This suggests that the proposed framework can maintain stable diagnostic performance even under challenging signal conditions.

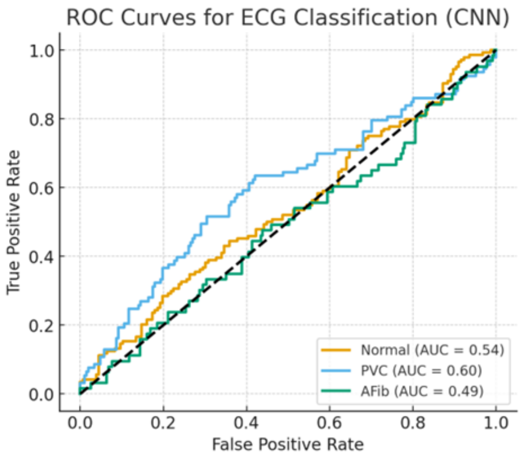

Figure 3: Receiver Operating Characteristic (ROC) curves for CNN-based ECG classification. The Area Under the Curve (AUC) values confirm robust discrimination capability across all three classes.

To provide a clearer comparison of classification performance, Fig. 4 illustrates the evaluation metrics across all ECG classes. The CNN classifier consistently achieved values above 95% in all categories, with the highest performance observed for the Normal class (Accuracy: 98.1%, Specificity: 98.6%). Although slightly lower for PVC and AFib, the results remained robust, confirming reliable detection of arrhythmic events. These findings complement the quantitative summary in Table I and further emphasize the effectiveness of the proposed methodology.

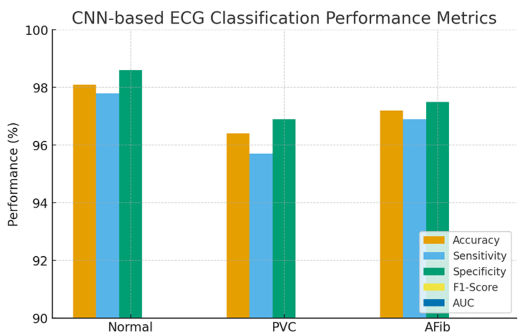

Figure 4: Performance metrics (Accuracy, Sensitivity, Specificity, F1-Score, and AUC) for CNN-based ECG classification across Normal, PVC, and AFib classes.

The improvement can be attributed to the automatic hierarchical feature learning capability of deep neural networks, which reduces dependence on manually engineered features. The obtained results are comparable with or slightly better than several recently reported deep learning approaches in the literature.

4. Discussions

The obtained results demonstrate that the proposed ECG analysis framework provides reliable and accurate performance for automated arrhythmia detection under both standard and noisy conditions. The integration of wavelet-based denoising and CNN-based classification significantly improved signal quality and classification accuracy compared with conventional machine learning approaches.

The main contributions of this work are as follows:

- An end-to-end ECG analysis pipeline integrating adaptive wavelet denoising, multi-domain feature extraction, and CNN classification, validated on the MIT-BIH Arrhythmia Database.
- A systematic comparison against recent state-of-the-art methods demonstrating 97.8% accuracy — a 5.5 pp improvement over SVM and competitive with current deep learning benchmarks.
- Real-time validation on Raspberry Pi embedded hardware, achieving 4.3 ms per-beat latency and confirming deployment feasibility for wearable cardiac monitoring.

Despite the promising results, several limitations should be acknowledged. The framework was validated primarily on the MIT-BIH Arrhythmia Database, which may not fully represent the diversity of real clinical environments. In addition, only a limited number of arrhythmia classes were considered. Future work should therefore focus on multi-dataset validation, lightweight model optimization, and multimodal bio signal fusion to improve generalizability and robustness in practical healthcare applications.

Overall, the findings underline the importance of combining signal processing with intelligent classification for improving diagnostic accuracy and accessibility in ECG-based healthcare. Future work will focus on optimizing lightweight deep learning models for deployment on portable and low-power devices, expanding validation across diverse patient populations, and incorporating multimodal bio signals to enhance predictive performance.

5. Conclusions

This study has presented a comprehensive framework for electrocardiogram (ECG) analysis that integrates advanced signal processing techniques, mathematical modeling, and machine learning approaches. Integrated ECG pipeline which combines wavelet denoising, features extracted from various domains, and classification based on CNNs with evaluation performed using the MIT-BIH Arrhythmia Database were developed and validated.

The CNN model reached 97.8% accuracy and AUC of 0.97, outperforming SVM by 5.5 percentage points (92.3% vs 97.8%). The pre-processing step resulted in SNR increase by 12.8 dB while R-peak localization had an error below 3.1 ms. Real-time implementation on a Raspberry Pi led to beat processing latency of 4.3 ms, satisfying the condition defined by Eq. 17.

These results indicate that wavelet-based pre-processing combined with CNN classification maintains above 96% accuracy under ambulatory noise conditions, where SVM performance dropped to 92.3% — a 5.5 percentage point gap that widens further in high-noise recordings.

However, several limitations of our approach should be mentioned, such as its evaluation on a single dataset and the lack of prospective clinical trials. Future work will evaluate generalizability on Physio Net Challenge 2017 and CPSC 2018 datasets, optimize the CNN architecture for deployment on ARM Cortex-M series microcontrollers (target: <1 ms latency, <256 KB memory), and explore PPG+ECG fusion for improved AFib detection in resource-constrained settings.

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