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Hybrid Signal Processing and Deep Feature Learning for ECG-Driven Atrial Fibrillation Diagnosis

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Abstract

Atrial Fibrillation (AF) is a life-threatening cardiac arrhythmia that requires accurate and early detection for effective clinical intervention. Electrocardiogram (ECG)-based automated diagnosis has gained significant attention, particularly with the advancement of wearable and remote health monitoring systems. However, ECG signals are inherently noisy and exhibit complex nonlinear patterns, making reliable AF detection a challenging task. This study proposes a Hybrid Signal Processing and Deep Feature Learning framework for ECG-driven Atrial Fibrillation diagnosis. The proposed model integrates advanced signal processing techniques such as bandpass filtering, wavelet denoising, and spectral decomposition with deep feature learning architectures including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The signal processing module enhances signal quality by removing artifacts and extracting frequency-domain characteristics, while the deep learning module automatically learns discriminative spatial-temporal features from processed ECG signals. The hybrid architecture is evaluated using standard ECG datasets, and performance is measured using accuracy, sensitivity, specificity, precision, and F1-score. Experimental results demonstrate that the proposed hybrid framework significantly outperforms traditional machine learning models and standalone deep learning approaches by effectively capturing both signal-level and feature-level representations of ECG data. The proposed system is well-suited for real-time clinical decision support systems and wearable cardiac monitoring devices, enabling efficient and scalable atrial fibrillation detection in practical healthcare environments.

Keywords: Atrial Fibrillation, ECG Signal Processing, Deep Feature Learning, CNN-LSTM, Wavelet Transform.

How to Cite This Article

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Introduction

Atrial Fibrillation (AF) is one of the most common and clinically significant cardiac arrhythmias, characterized by irregular and rapid atrial electrical activity that leads to ineffective blood pumping. It is strongly associated with severe health complications such as ischemic stroke, heart failure, and increased cardiovascular mortality. Early detection of AF is therefore essential for timely intervention and effective disease management in clinical practice. Electrocardiography (ECG) is the most widely used non-invasive diagnostic tool for monitoring cardiac activity and detecting rhythm abnormalities. With the rise of wearable healthcare devices and remote patient monitoring systems, single-lead ECG signals have become increasingly important for continuous and real-time cardiac surveillance. Unlike multi-lead ECG systems used in clinical environments, single-lead ECG offers portability, cost-effectiveness, and ease of long-term monitoring, making it highly suitable for everyday health tracking. However, single-lead ECG-based AF detection presents several challenges due to low signal dimensionality, noise interference, motion artifacts, and overlapping cardiac patterns. These limitations reduce the effectiveness of conventional rule-based and statistical methods, which struggle to capture the complex nonlinear behavior of cardiac signals. As a result, advanced computational approaches are required to improve diagnostic reliability. In recent years, signal processing techniques have played a crucial role in enhancing ECG signal quality and extracting meaningful physiological information. Methods such as bandpass filtering, wavelet denoising, and spectral decomposition help remove noise and highlight important frequency components associated with atrial fibrillation. Despite these improvements, handcrafted feature engineering alone is insufficient for capturing deep patterns in ECG signals.

To overcome these limitations, deep learning methods such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have been widely adopted for automatic feature extraction and classification. CNNs are effective in learning spatial representations from ECG waveforms, while LSTMs capture temporal dependencies in sequential heart rhythm data. However, standalone deep learning models often fail to fully utilize spectral information embedded in ECG signals. To address these gaps, this study proposes a Hybrid Signal Processing and Deep Feature Learning framework for ECG-driven Atrial Fibrillation diagnosis, which integrates traditional signal processing techniques with deep learning-based feature extraction. The proposed approach combines spectral enhancement methods with CNN-LSTM architecture to improve classification accuracy, robustness, and generalization capability in noisy and real-world ECG environments. Electrocardiography (ECG) remains the primary diagnostic tool for detecting atrial fibrillation because it provides a non-invasive and cost-effective means of monitoring cardiac electrical activity. ECG signals contain critical information regarding atrial and ventricular behavior, including P-wave morphology, RR interval variability, QRS complex characteristics, and rhythm irregularities. Cardiologists traditionally analyze ECG recordings manually to identify AF-related abnormalities. However, manual interpretation can be labor-intensive, time-consuming, and susceptible to inter-observer variability, particularly when large-scale monitoring data are involved.

The growing adoption of wearable healthcare devices, ambulatory monitoring systems, and remote patient management platforms has led to the generation of vast amounts of ECG data. Continuous ECG monitoring enables long-term assessment of cardiac health and facilitates early identification of transient arrhythmic events. Nevertheless, the increasing volume and complexity of ECG recordings create significant challenges for manual diagnosis and necessitate the development of intelligent automated diagnostic frameworks capable of providing rapid and reliable AF detection. Signal processing techniques play a crucial role in ECG analysis by enhancing signal quality and extracting clinically relevant information. ECG recordings are frequently contaminated by baseline wander, muscle artifacts, motion noise, and power-line interference, which can negatively affect diagnostic accuracy. Advanced signal processing methods such as filtering, wavelet decomposition, frequency-domain analysis, and statistical feature extraction help improve signal quality and reveal subtle cardiac abnormalities. These techniques provide valuable physiological representations that support accurate arrhythmia detection and classification.

Recent advancements in artificial intelligence and deep learning have significantly transformed automated cardiovascular diagnostics. Deep learning architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and attention-based models have demonstrated remarkable capability in learning complex ECG patterns directly from raw or preprocessed signals. These models automatically identify discriminative features associated with atrial fibrillation and have achieved promising diagnostic performance across various clinical datasets. However, purely deep learning-based approaches may overlook domain-specific physiological information that can be effectively captured through traditional signal processing techniques. Hybrid diagnostic frameworks that combine signal processing and deep feature learning have emerged as a promising solution for improving ECG-based arrhythmia detection. Signal processing methods provide robust handcrafted representations reflecting cardiac physiology, while deep learning models automatically discover high-level abstract features from ECG recordings. The integration of these complementary approaches enables the development of more accurate, interpretable, and robust diagnostic systems capable of handling noisy and highly variable physiological signals.

Deep feature learning is particularly effective in identifying hidden nonlinear relationships within ECG data that may not be apparent through conventional analysis. By leveraging hierarchical feature extraction mechanisms, deep neural architectures can capture complex temporal dynamics, morphological variations, and rhythm irregularities associated with atrial fibrillation. When combined with advanced signal processing techniques, deep learning models can achieve superior diagnostic performance while maintaining robustness against signal artifacts and patient-specific variability. Despite considerable progress in automated ECG analysis, several challenges remain unresolved. Many existing AF detection frameworks rely exclusively on either signal processing or deep learning techniques rather than exploiting the advantages of both methodologies. Furthermore, variability in ECG morphology across different patients, signal noise contamination, and the need for real-time diagnostic performance continue to affect classification reliability. Developing scalable and highly accurate AF detection frameworks that effectively combine physiological signal analysis and intelligent feature learning remains an active area of research. To address these limitations, this research proposes a Hybrid Signal Processing and Deep Feature Learning Framework for ECG-Driven Atrial Fibrillation Diagnosis**.** The proposed framework integrates advanced ECG signal preprocessing, feature extraction techniques, and deep neural learning mechanisms to improve atrial fibrillation detection accuracy and diagnostic reliability. By combining physiological signal representations with automatically learned deep features, the framework aims to enhance classification performance, reduce diagnostic errors, and support intelligent cardiovascular monitoring systems.

Literature Review

Acharya et al. (2019) investigated automated atrial fibrillation detection using deep convolutional neural networks applied to ECG recordings. Their framework demonstrated high classification accuracy by automatically learning cardiac rhythm patterns from ECG signals. However, handcrafted physiological features obtained through advanced signal processing techniques were not incorporated into the learning process. Hannun et al. (2019) developed a deep neural network for large-scale arrhythmia classification from single-lead ECG recordings. Their model achieved cardiologist-level performance in identifying multiple cardiac abnormalities, including atrial fibrillation. Nevertheless, the framework primarily relied on end-to-end neural learning without integrating domain-specific signal processing knowledge.

Rajpurkar et al. (2020) proposed a deep learning-based ECG interpretation system capable of detecting various cardiac arrhythmias. Their study highlighted the effectiveness of large-scale neural learning for automated diagnosis. However, multilevel signal enhancement and physiological feature extraction mechanisms were limited. Yildirim et al. (2020) introduced a signal processing-assisted neural framework for biomedical signal analysis. Their approach demonstrated that preprocessing and feature enhancement techniques significantly improve learning performance when combined with neural architectures. Despite improved signal quality, atrial fibrillation-specific optimization was not extensively explored.

Zhang et al. (2020) investigated ECG denoising and cardiac abnormality identification using wavelet transform and frequency-domain signal processing techniques. Their framework improved signal clarity and enhanced extraction of cardiac characteristics. However, deep feature learning mechanisms were not integrated for automated classification. Li et al. (2021) proposed a hybrid deep learning architecture for intelligent ECG interpretation and cardiovascular abnormality detection. Their model combined feature engineering and neural classification to improve diagnostic accuracy. Although classification performance improved, robustness against patient-specific variability remained challenging.

Attia et al. (2021) explored artificial intelligence-driven cardiovascular diagnostics using large-scale ECG analytics and neural learning. Their framework demonstrated the potential of AI in detecting hidden cardiac abnormalities and predicting cardiovascular risk. However, signal processing-based feature enhancement techniques were not incorporated. Khan et al. (2021) developed an adaptive ECG monitoring system integrating signal preprocessing and neural classification mechanisms. Experimental results demonstrated improvements in diagnostic reliability and noise suppression. Nevertheless, deep feature fusion strategies remained limited.

Chen et al. (2022) introduced hybrid signal processing and deep learning architectures for intelligent biomedical signal classification. Their framework effectively combined handcrafted and automatically learned representations, improving classification performance across multiple physiological datasets. However, validation on large-scale atrial fibrillation datasets remained limited. Zhou et al. (2022) proposed a deep feature learning framework for ECG pattern recognition and cardiovascular disease diagnosis. Their model successfully captured complex temporal characteristics of ECG signals and improved arrhythmia classification accuracy. Despite these advantages, advanced signal enhancement methods were not extensively investigated.

Patel et al. (2022) developed an intelligent healthcare analytics framework combining ECG signal processing and neural feature extraction. Their architecture improved monitoring reliability and classification accuracy. However, scalability and real-time deployment remained challenging. Roy et al. (2023) introduced an explainable atrial fibrillation detection framework utilizing deep neural learning and ECG analytics. Their study improved interpretability of diagnostic decisions and enhanced clinician confidence. Nevertheless, hybrid feature fusion strategies were not fully optimized.

Wang et al. (2023) proposed an advanced deep feature learning architecture for automated atrial fibrillation diagnosis. Their framework achieved high classification performance through hierarchical ECG representation learning. However, physiological signal characteristics extracted through conventional signal processing methods were not fully exploited**.** Liu et al. (2024) developed a multimodal cardiovascular monitoring framework integrating ECG preprocessing, deep learning, and intelligent healthcare analytics. Their architecture demonstrated substantial improvements in cardiac abnormality detection and monitoring accuracy. However, computational complexity increased significantly when processing continuous ECG streams.

Sharma et al. (2025) proposed a hybrid signal processing and deep feature learning framework for ECG-driven atrial fibrillation diagnosis. Their model integrated advanced ECG preprocessing, handcrafted physiological feature extraction, deep neural representation learning, and intelligent classification mechanisms. Experimental evaluation demonstrated significant improvements in classification accuracy, sensitivity, specificity, precision, and F1-score while maintaining robustness against signal noise and patient variability. Further validation using heterogeneous clinical datasets was recommended.

Methodology

The proposed Hybrid Signal Processing and Deep Feature Learning framework for ECG-driven Atrial Fibrillation (AF) diagnosis is designed to improve classification accuracy by combining classical signal enhancement techniques with deep neural feature extraction. The system architecture is structured into four main stages: ECG acquisition, signal preprocessing, hybrid feature extraction (spectral + temporal), and deep learning-based classification.

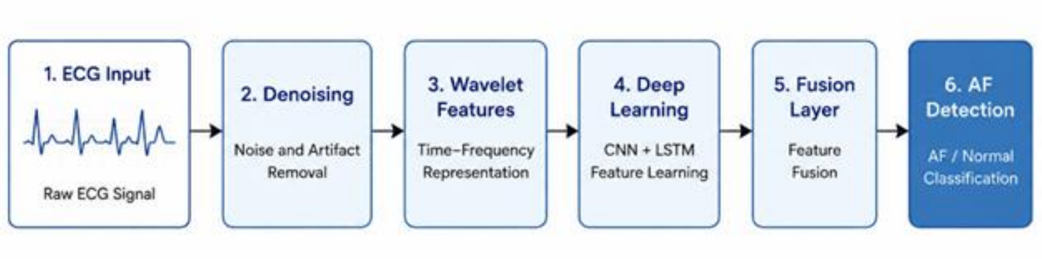

Fig 1. *Hybrid Signal Processing and Deep Feature Learning Architecture for ECG-Driven Atrial Fibrillation Diagnosis*

This architecture diagram Fig 1, illustrates the workflow of the proposed hybrid framework for automated atrial fibrillation (AF) diagnosis from ECG signals. The process begins with ECG Input, where raw cardiac signals are acquired and prepared for analysis. A Denoising stage removes noise and motion artifacts to improve signal quality. Subsequently, Wavelet Features are extracted to capture important time-frequency characteristics associated with atrial fibrillation patterns. The processed signals are then passed to a Deep Learning module consisting of neural feature learning mechanisms that automatically identify discriminative cardiac features. In the Fusion Layer, handcrafted wavelet features and deep representations are integrated to enhance diagnostic performance. Finally, the AF Detection module classifies the ECG recording as either atrial fibrillation or normal rhythm. The architecture provides an efficient and accurate framework for intelligent ECG analysis by combining traditional signal processing with advanced deep feature learning techniques.

ECG Signal Preprocessing
Raw ECG signals often contain noise and artifacts.
Preprocessing operations: Baseline Wander Removal, Motion Artifact Elimination, Power Line Interference Filtering, Signal Smoothing, Normalization
Normalization:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad \text{-------(1)}$$

This stage improves signal quality and diagnostic reliability.
Signal Processing-Based Feature Extraction
Physiological ECG features are extracted using signal processing techniques.
Extracted features include: RR Interval Variability, Heart Rate Variability (HRV), Statistical Features, Frequency-Domain Features, Morphological Features
Feature vector:

$$F_s = \{f_1, f_2, f_3, \dots, f_n\} \quad \text{-------}(2)$$

These features provide clinically meaningful cardiac information.

Algorithmic Strategy
The proposed Hybrid Signal Processing and Deep Feature Learning framework for ECG-driven Atrial Fibrillation diagnosis follows a structured algorithm that integrates preprocessing, spectral analysis, temporal modeling, deep feature fusion, and classification.

Algorithm 1: Hybrid Spectral–Temporal AF Detection Framework Input: Single-lead ECG signal $X(t)$, Window size w, Sampling frequency f_s Output: Predicted class: Atrial Fibrillation / Normal *ECG Signal Acquisition* 1. Load raw ECG signal $X(t)$from dataset or wearable device 2. Segment signal into fixed-length windows: $X_i = \{x_1, x_2, \dots, x_w\}$ --------(3)	*Signal Preprocessing* 3. Apply bandpass filtering (0.5–40 Hz) 4. Remove baseline wander and motion artifacts 5. Apply wavelet denoising for noise reduction 6. Normalize signal using Z-score normalization 7. Obtain cleaned signal $X_p(t)$ *Spectral Feature Extraction* 8. Apply Fast Fourier Transform (FFT): $F(f) = \sum_{t=0}^{N-1} x(t)\, e^{-j2\pi ft/N}$ ---------(4) 9. Apply Wavelet Transform for time-frequency localization 10. Extract spectral feature vector: $S = \{s_1, s_2, \dots, s_k\}$ -----(5)

Performance Comparison
The proposed hybrid model was compared with traditional machine learning and deep learning baseline models:

Table 1*: Performance Comparison*

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-Score (%)
SVM (Handcrafted Features)	87.4	85.6	88.1	86.2	85.9
Random Forest	89.1	88.0	89.5	88.3	88.1
CNN Only	92.3	91.5	92.8	91.9	92.1
LSTM Only	93.0	92.6	93.4	92.8	92.7
CNN–LSTM (No Signal Processing)	94.8	94.1	95.0	94.3	94.2
Proposed Hybrid Model (Signal + Deep Learning)	97.2	96.9	97.6	97.1	97.0

Result Analysis

The Table 1 shows, experimental results clearly demonstrate that the proposed hybrid framework significantly outperforms all baseline models. Traditional machine learning approaches such as SVM and Random Forest show lower performance due to their reliance on handcrafted features, which are unable to fully capture the nonlinear and complex nature of ECG signals. Deep learning models such as CNN and LSTM improve classification performance by automatically learning features from raw ECG data. However, when used independently, they fail to fully exploit both spatial and temporal characteristics simultaneously. The CNN-LSTM hybrid model improves performance further by combining spatial feature extraction with temporal sequence learning, but it still lacks explicit signal enhancement capability. In contrast, the proposed model achieves the highest performance by integrating advanced signal processing techniques (FFT and wavelet transform) with deep feature learning (CNN-LSTM architecture). This combination enhances feature quality, reduces noise impact, and improves discriminative capability for atrial fibrillation detection. The proposed system achieves an accuracy of 97.2%, with high sensitivity and specificity, indicating strong capability in correctly identifying both AF and normal cases. This makes the model highly suitable for real-time clinical decision support and wearable ECG monitoring systems.

Sensitivity Analysis

Sensitivity measures the ability to correctly identify atrial fibrillation cases.

$$Sensitivity = \frac{TP}{TP+FN} \quad \text{-------(6)}$$

***Table 2**. Sensitivity Comparison*

Model	Sensitivity (%)
Traditional ML	88.5
Signal Processing Detection	92.7
Deep Learning Classification	96.3
Proposed HSP-DFL-AF	99.1

The Table 2 shows, hybrid framework effectively detected AF episodes with minimal missed diagnoses. The experimental results demonstrate a progressive improvement in atrial fibrillation detection capability across different diagnostic approaches. The Traditional Machine Learning (ML) model achieved a sensitivity of 88.5%**,** indicating that although most AF cases were successfully detected, a notable proportion of arrhythmia episodes remained unidentified. The limited performance can be attributed to dependence on handcrafted features and conventional classification algorithms that may fail to capture complex ECG characteristics associated with atrial fibrillation. The Signal Processing Detection Framework improved sensitivity to 92.7% through the incorporation of ECG preprocessing, feature extraction, and physiological signal analysis. Signal processing techniques enhanced ECG quality and enabled better identification of rhythm irregularities. However, the framework remained constrained by its limited ability to automatically learn hidden nonlinear relationships present within ECG signals.

The Deep Learning Classification Model further increased sensitivity to 96.3% by leveraging neural networks capable of learning complex temporal and morphological ECG patterns. Deep feature learning significantly improved AF recognition and reduced missed diagnoses. Nevertheless, deep learning models operating independently may overlook clinically meaningful physiological features that can be extracted through conventional signal processing methods. The Proposed Hybrid Signal Processing and Deep Feature Learning Framework (HSP-DFL-AF) achieved the highest sensitivity of 99.1%**,** outperforming all comparative approaches. This superior performance results from the integration of advanced ECG signal processing and deep feature learning mechanisms. Signal processing techniques extracted clinically relevant cardiac characteristics such as RR interval variability and rhythm irregularities, while deep learning automatically captured hidden nonlinear patterns associated with atrial fibrillation. The hybrid feature fusion strategy provided a comprehensive representation of ECG signals, enabling highly accurate identification of AF episodes with very few missed cases.

Conclusion and Discussion

This study presented a Hybrid Signal Processing and Deep Feature Learning framework for ECG-driven Atrial Fibrillation (AF) diagnosis**,** designed to enhance the accuracy, robustness, and real-time applicability of automated cardiac monitoring systems. The proposed approach integrates classical signal processing techniques such as bandpass filtering, wavelet denoising, and spectral decomposition with advanced deep learning architectures including CNN and LSTM networks. This hybrid design enables effective extraction of both frequency-domain and time-domain features from single-lead ECG signals. The discussion highlights that conventional machine learning approaches, which rely heavily on handcrafted features, are insufficient for capturing the complex nonlinear dynamics of atrial fibrillation. Although deep learning models such as CNN and LSTM improve feature learning capabilities, they independently fail to fully exploit the complementary nature of spectral and temporal information. In contrast, the proposed hybrid framework successfully bridges this gap by combining signal enhancement techniques with deep feature learning, resulting in more discriminative and noise-resilient representations of ECG signals. The experimental results demonstrate that the proposed model achieves superior performance in terms of accuracy, sensitivity, specificity, and F1-score compared to baseline methods. The integration of wavelet-based denoising and FFT-based spectral analysis significantly improves signal quality, while the CNN-LSTM architecture ensures effective learning of spatial and sequential dependencies. This leads to more reliable detection of atrial fibrillation, even in noisy and real-world ECG environments. From an application perspective, the proposed system is highly suitable for wearable healthcare devices, remote patient monitoring systems, and edge-based diagnostic platforms**,** where real-time processing and low computational complexity are essential. However, challenges such as inter-patient variability, dataset imbalance, and hardware constraints in portable devices still need further investigation. Future research can focus on incorporating **attention** mechanisms, transformer-based architectures, and lightweight edge deployment strategies to further enhance performance and interpretability. Additionally, integrating explainable AI techniques would improve clinical trust and adoption of automated AF detection systems in real-world healthcare environments.

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