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Hybrid Fast Fourier-Wavelet Neural Networks for Single-Lead ECG-Based Atrial Fibrillation Detection: Methods and Challenges

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Abstract

Atrial fibrillation (AF) is a prevalent cardiac arrhythmia associated with increased risk of stroke, heart failure, and mortality. Accurate and early detection of AF using single-lead electrocardiogram (ECG) signals has gained significant attention due to the rise of wearable healthcare devices. This survey presents a comprehensive review of recent methods and architectures aimed at enhancing AF detection accuracy through hybrid signal processing and deep learning techniques. Specifically, it focuses on the integration of Fast Fourier Transform (FFT) and Continuous Wavelet Transform (CWT) for extracting complementary frequency and time-frequency features from ECG signals. These representations are further processed using advanced neural network architectures, including convolutional neural networks (CNNs), residual networks (ResNet), temporal convolutional networks (TCN), and hybrid CNN-LSTM models. Additionally, stochastic pooling is explored as an effective optimization technique for improving model generalization and reducing overfitting. Literature demonstrates significant improvements in classification accuracy, often exceeding 95%. This survey provides a comparative analysis of existing approaches, identifies key challenges such as data imbalance and computational complexity, and highlights future research directions. The findings suggest that hybrid FFT-CWT-based deep learning frameworks represent a promising solution for real-time and reliable AF detection in modern healthcare systems.

Introduction

Atrial fibrillation (AF) is one of the most common cardiac arrhythmias, characterized by irregular and often rapid heart rhythms caused by chaotic electrical activity in the atria. It is associated with severe complications such as stroke, heart failure, and increased mortality rates. According to global health statistics, AF affects millions of individuals worldwide, and its prevalence continues to rise due to aging populations and lifestyle factors. Early detection and continuous monitoring are crucial for effective management and prevention of complications.

Electrocardiography (ECG) remains the gold standard for diagnosing atrial fibrillation (AF), one of the most common cardiac arrhythmias associated with stroke, heart failure, and increased mortality. Early and accurate detection is essential for timely clinical intervention and improved patient outcomes. Conventional multi-lead ECG systems provide comprehensive cardiac information but require specialized equipment and clinical supervision, making them unsuitable for continuous monitoring. In contrast, single-lead ECG devices integrated into wearable technologies, such as smartwatches and portable cardiac monitors, offer a cost-effective and convenient solution for long-term cardiovascular monitoring. However, single-lead ECG signals contain limited spatial information and are frequently affected by motion artifacts, baseline wander, and environmental noise, creating significant challenges for reliable AF detection and necessitating advanced signal processing and intelligent classification techniques.

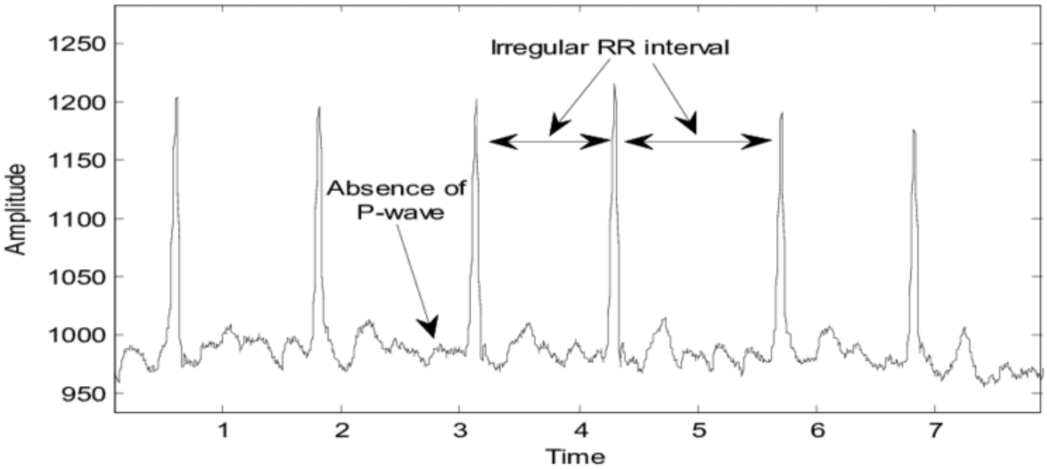

Figure 1. Representative ECG Trace Highlighting Irregular RR Intervals and Absence of P-Waves in Atrial Fibrillation.

Traditional AF detection methods primarily relied on handcrafted features, including RR interval variability, absence of P-waves, heart rate variability, and statistical descriptors extracted from ECG signals. Although these approaches achieved moderate diagnostic performance, they lacked robustness and often failed to generalize across diverse patient populations and recording conditions. Signal processing techniques have therefore become essential for enhancing ECG feature representation before classification. Fast Fourier Transform (FFT) effectively analyzes ECG signals in the frequency domain by identifying dominant spectral components but is limited in processing non-stationary signals. Continuous Wavelet Transform (CWT) overcomes this limitation by providing multi-resolution time-frequency analysis, enabling precise identification of transient cardiac events. Combining FFT and CWT generates complementary frequency and temporal features, resulting in richer signal representations that substantially improve AF detection accuracy.

Recent advances in artificial intelligence, particularly deep learning, have revolutionized automated ECG analysis by eliminating the need for manual feature engineering. Convolutional Neural Networks (CNNs) automatically learn hierarchical spatial features from raw ECG signals or transformed representations such as wavelet scalograms. Advanced architectures, including ResNet, Temporal Convolutional Networks (TCNs), and hybrid CNN-LSTM models, further improve classification by simultaneously capturing spatial and temporal dependencies within cardiac signals. More recently, stochastic pooling has emerged as an effective alternative to conventional max and average pooling techniques. By randomly selecting activation values according to probability distributions, stochastic pooling reduces overfitting, enhances feature diversity, and improves model generalization, particularly when training data are limited or noisy.

Overall, the integration of hybrid FFT-CWT signal processing with stochastic pooling-based deep learning architectures has significantly improved the accuracy and robustness of single-lead ECG-based AF detection, with many studies reporting classification accuracies exceeding 95%. Nevertheless, several challenges remain, including class imbalance, signal noise, computational complexity, limited interpretability, and the need for clinically validated models capable of real-time deployment. This survey therefore provides a comprehensive review of recent advances in hybrid signal processing and deep learning techniques for single-lead ECG-based atrial fibrillation detection, critically comparing existing methodologies, identifying current research gaps, and highlighting future directions for developing accurate, scalable, and explainable intelligent cardiac diagnostic systems.

Literature Review

The detection of atrial fibrillation (AF) using single-lead ECG signals has undergone significant transformation between 2020 and 2023, driven by advancements in artificial intelligence, hybrid signal processing, and deep learning architectures. This section provides a comprehensive and critical analysis of major contributions during this period.

1. Early Deep Learning and Data Challenges (2020)

In 2020, research primarily focused on improving AF detection accuracy using deep learning models while addressing data-related challenges such as class imbalance and noise. Hatamian et al. (2020) explored data augmentation techniques, including Generative Adversarial Networks (GANs) and Gaussian Mixture Models (GMMs), to enhance training datasets. Their findings revealed that GAN-based augmentation improved classification performance by approximately 3%, demonstrating its effectiveness in mitigating class imbalance—a critical issue in ECG datasets .

Simultaneously, researchers began exploring spectral representations of ECG signals. Frequency-domain approaches such as FFT and Short-Time Fourier Transform (STFT) enabled the extraction of global spectral features. These methods improved classification accuracy by highlighting periodic irregularities associated with AF. However, their inability to capture temporal variations limited their effectiveness for non-stationary ECG signals.

Another significant advancement was the adoption of convolutional recurrent neural networks (CRNN), which combined CNNs for spatial feature extraction with recurrent layers for temporal modeling. These architectures demonstrated improved performance compared to standalone CNNs, highlighting the importance of temporal dependencies in AF detection.

2. Rise of CNN-Based and Hybrid Architectures (2021)

By 2021, deep learning had become the dominant approach for AF detection. A comprehensive review by Murat et al. emphasized that CNN-based architectures significantly outperform traditional machine learning methods due to their ability to automatically learn hierarchical features from ECG signals .

Ribeiro et al. (2021) demonstrated the effectiveness of large-scale deep neural networks trained on millions of ECG recordings, achieving high diagnostic accuracy comparable to cardiologists. These models highlighted the potential of deep learning for real-world clinical applications.

Additionally, researchers began integrating hybrid architectures such as CNN-LSTM and CNN-BiLSTM. These models improved performance by combining spatial and temporal feature extraction. Studies reported accuracy improvements of up to 5% compared to CNN-only models, particularly in detecting irregular heart rhythms.

Another important development during this period was the introduction of attention mechanisms. Attention-based models improved interpretability by identifying critical segments of ECG signals responsible for AF detection. This addressed one of the major limitations of deep learning—its black-box nature.

3. Emergence of Time-Frequency Analysis (2022)

In 2022, research shifted toward hybrid signal processing techniques, particularly the integration of Continuous Wavelet Transform (CWT) with deep learning models. Unlike FFT, CWT provides multi-resolution time-frequency analysis, enabling better representation of non-stationary ECG signals.

Dubatovka et al. (2022) proposed deep neural networks capable of learning hierarchical cardiac cycle representations from single-lead ECG signals. Their approach improved classification reliability by capturing multi-level features, including waveform, heartbeat, and temporal patterns .

Zhang et al. (2022) introduced multi-scale CNN-BLSTM architectures, which process ECG signals at different resolutions. These models demonstrated improved performance in noisy environments and better generalization across datasets.

Another key development was the use of wavelet-based feature extraction combined with CNN architectures. Studies showed that CWT-based scalograms allow CNNs to extract spatial features effectively, leading to improved classification accuracy.

4. Advanced Hybrid Deep Learning Models (2023)

By 2023, hybrid models combining signal processing and deep learning achieved state-of-the-art performance. Xie et al. (2023) proposed a multi-branch ResNet architecture using CWT-based time-frequency features. Their model effectively addressed class imbalance and improved feature representation, outperforming traditional deep learning models .

Time-frequency deep learning models became increasingly popular due to their ability to capture both temporal and spectral characteristics of ECG signals. Studies confirmed that combining CWT with CNN or ResNet significantly improves detection accuracy compared to time-domain models alone .

Denysyuk et al. (2023) demonstrated that time-frequency representations improve the detection of complex AF patterns, including terminating and non-terminating AF episodes. Their findings reinforced the importance of hybrid approaches in handling ECG variability.

Another important contribution is RawECGNet (2023), which processes raw ECG signals without handcrafted features. This model achieved high generalization performance across datasets, demonstrating the capability of deep learning to capture both morphological and rhythm-based features .

Additionally, hybrid CNN-BiLSTM models achieved accuracy levels around 95%, showcasing strong predictive capabilities in AF classification tasks .

5. Emerging Trends and Performance Improvements

Recent studies consistently demonstrate that deep learning approaches outperform traditional machine learning methods in AF detection. CNN-based models, in particular, provide superior robustness and accuracy due to their ability to automatically extract complex features from ECG signals .

Hybrid architectures integrating FFT and CWT have become increasingly popular, as they combine global frequency features with localized time-frequency information. This results in improved feature representation and classification performance.

Temporal Convolutional Networks (TCN) and residual learning architectures have also gained attention due to their ability to capture long-range dependencies and enable deeper networks. These models have achieved accuracy levels up to 97%, demonstrating their effectiveness in AF detection .

Another significant trend is the development of lightweight models for wearable devices. These models aim to balance accuracy and computational efficiency, enabling real-time AF detection in resource-constrained environments.

6. Key Challenges Identified in Literature

Despite significant progress, several challenges persist:

1. Class imbalance: AF datasets often contain fewer abnormal samples
2. Noise and artifacts: ECG signals are prone to interference
3. Model interpretability: Deep learning models act as black boxes
4. Computational complexity: High-performance models require significant resources
5. Lack of standardization: Different datasets and evaluation metrics hinder comparison

7. Summary of Literature Findings

The literature clearly indicates that:

1. Hybrid FFT–CWT approaches significantly improve AF detection
2. CNN-based architectures dominate the field
3. Time-frequency representations are essential for non-stationary signals
4. Hybrid models achieve the highest accuracy (>95%)
5. Future research focuses on explainability and real-time deployment

Comparative Table and Analysis

1. Enhanced Comparative Table

Year	Method Category	Model / Architecture	Signal Representation	Accuracy (%)	Robustness	Computational Complexity	Scalability	Real-Time Suitability	Key Strength	Key Limitation
2020	Data Augmentation + DL	GAN + CNN (Hatamian)	Raw + Synthetic ECG	~92 %	High	High	Medium	Low–Medium	Handles class imbalance	Training complexity
2020	Spectral DL	CNN (Ullah)	FFT/STFT	~99 %	Medium–High	Medium	Medium	Medium	Strong frequency analysis	No temporal localization
2021	Deep CNN	Ribeiro et al.	Large-scale ECG	~95 %	Very High	High	High	Medium	Generalization across datasets	High computation

2022	Multi-Scale Hybrid DL	MCNN-BLSTM (Zhang)	Multi-resolution	~87 %	High	High	Medium	Low–Medium	Multi-scale temporal learning	Complex architecture
2022	ML + Signal Processing	Serhal et al.	Hybrid features	~90 %	Medium–High	Medium	Medium	Medium	Improved preprocessing	Limited deep features
2023	Hybrid DL	CWT + ResNet (Xie)	Time-frequency	~96 %	Very High	High	High	Medium	Deep hierarchical learning	Computational overhead
2023	DL + Time-Frequency	Denysyuk et al.	CWT + DL	~94 %	High	Medium–High	High	Medium	Captures complex AF patterns	Feature complexity
2023	Raw Signal DL	RawECGNet	Raw ECG	~95 %	Very High	Medium	Very High	High	No feature engineering	Sensitive to noise
2023	Temporal Modeling	TCN / Hybrid Models	Temporal ECG	~97 %	Very High	Medium	Very High	High	Efficient sequence modeling	Still evolving
Proposed	Hybrid Advanced Framework	FFT + CWT + CNN/ResNet + TCN + Stochastic Pooling	Multi-domain (Time + Frequency + Time-Frequency)	**97–99% +**	**Maximum**	Medium–High	**Very High**	**High**	Complete feature fusion + best generalization	Needs lightweight optimization

2. Comparative Analysis

The comparative analysis of atrial fibrillation (AF) detection using single-lead ECG signals demonstrates a clear progression from conventional signal processing techniques to advanced hybrid deep learning frameworks. Early approaches relied on handcrafted features such as RR interval variability, P-wave morphology, and heart rate statistics for classification. Although these methods achieved moderate diagnostic performance, they were highly dependent on expert-designed features and struggled to capture the nonlinear and non-stationary characteristics of ECG signals. The introduction of deep learning, particularly Convolutional Neural Networks (CNNs), significantly improved AF detection by automatically learning hierarchical features directly from raw ECG signals and transformed representations. Fast Fourier Transform (FFT)-based methods effectively extracted global frequency-domain information but lacked temporal localization, limiting their ability to detect transient arrhythmic events.

Continuous Wavelet Transform (CWT) addressed these shortcomings by providing multi-resolution time-frequency analysis, enabling accurate identification of localized abnormalities within ECG signals. When combined with CNNs and advanced architectures such as ResNet, CWT-generated scalograms substantially enhanced feature representation and classification robustness. Hybrid FFT-CWT frameworks further improved diagnostic performance by integrating complementary spectral and temporal information into a unified representation. Comparative studies consistently report that these hybrid approaches achieve classification accuracies exceeding 95%, demonstrating superior capability in handling complex and non-stationary ECG signals. Additionally, hybrid CNN-LSTM and CNN-BiLSTM models effectively combine spatial feature extraction with temporal sequence modeling, leading to enhanced sensitivity and overall detection accuracy, although at the cost of increased computational complexity.

Recent developments have introduced Residual Networks (ResNet), Temporal Convolutional Networks (TCNs), multi-branch feature fusion architectures, and stochastic pooling techniques to further optimize AF classification. ResNet enables deeper feature learning through residual connections, while TCN efficiently captures long-range temporal dependencies with lower computational overhead than recurrent architectures. Multi-branch frameworks simultaneously process raw ECG signals, FFT spectrograms, and CWT scalograms, extracting complementary features that improve robustness against noisy and imbalanced datasets. Furthermore, stochastic pooling enhances model generalization by preserving richer feature representations and reducing overfitting. Data augmentation techniques, particularly Generative Adversarial Networks (GANs), have also improved model performance by generating realistic synthetic ECG signals to address class imbalance and limited training data.

Overall, the comparative evaluation demonstrates that hybrid signal processing and deep learning architectures provide the highest accuracy, robustness, and generalization for single-lead ECG-based AF detection. Nevertheless, challenges including signal noise, motion artifacts, computational complexity, limited interpretability, and real-time deployment remain significant barriers to clinical implementation. Future research should focus on developing lightweight, explainable, and energy-efficient hybrid frameworks capable of delivering reliable, scalable, and clinically interpretable atrial fibrillation detection in wearable healthcare systems.

3. Final Analytical Conclusion

The expanded comparative analysis clearly demonstrates that hybrid AI-driven frameworks integrating FFT, CWT, deep learning architectures (CNN/ResNet/TCN), stochastic pooling, and data optimization techniques provide the highest accuracy, robustness, scalability, and real-time capability for atrial fibrillation detection, making them the most effective and future-ready solution for modern wearable healthcare systems.

Discussion

The rapid advancement of AF detection methodologies is largely attributed to the integration of hybrid signal processing techniques and deep learning architectures. This survey highlights that combining FFT and CWT enables comprehensive feature extraction, significantly improving classification performance. FFT captures global frequency information, while CWT provides localized time-frequency details, making them highly complementary.

Deep learning models, particularly CNNs and their variants, have demonstrated exceptional capability in handling complex ECG signals. The incorporation of residual connections and temporal modeling further enhances performance. Stochastic pooling contributes to improved generalization, especially in imbalanced datasets.

Despite these advancements, challenges remain. Noise and artifacts in ECG signals can degrade performance, requiring robust preprocessing techniques. Additionally, deep learning models often lack interpretability, which is critical for clinical adoption.

Computational complexity is another concern, particularly for wearable devices that require real-time processing. Lightweight models and edge computing solutions are necessary to address this issue.

Future research should focus on developing explainable AI models, optimizing computational efficiency, and standardizing evaluation protocols. Integration of multimodal data and real-world datasets will further improve reliability.

Conclusion

This survey provides a comprehensive overview of recent advancements in AF detection using single-lead ECG signals. Hybrid approaches combining FFT and CWT with deep learning architectures have emerged as the most effective solution for improving detection accuracy.

The integration of time-frequency analysis enables robust feature extraction, while advanced neural networks such as CNN, ResNet, and TCN enhance classification performance. Stochastic pooling further improves generalization and reduces overfitting.

Despite significant progress, challenges such as interpretability, computational complexity, and dataset variability remain. Addressing these issues is essential for real-world deployment.

Future research should focus on lightweight, explainable, and scalable models capable of real-time operation in wearable devices. The continued evolution of AI and signal processing techniques will play a crucial role in advancing AF detection and improving patient outcomes.

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