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Hybrid Deep Learning Approaches for Single-Lead ECG-Based Atrial Fibrillation Detection

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Abstract

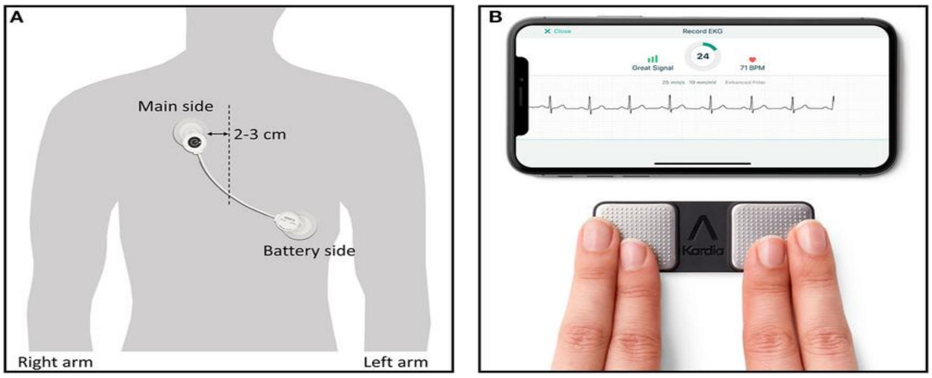
Atrial fibrillation (AF) is one of the most prevalent cardiac arrhythmias, significantly contributing to stroke, heart failure, and mortality worldwide. Early and accurate detection is essential for effective treatment and prevention. Recent advancements in artificial intelligence and signal processing techniques have enabled improved AF detection using single-lead electrocardiogram (ECG) signals. This systematic review focuses on hybrid approaches combining Fast Fourier Transform (FFT) and Continuous Wavelet Transform (CWT) with stochastic pooling-based neural networks for enhanced classification accuracy. The integration of FFT enables efficient frequency-domain feature extraction, while CWT provides superior time–frequency localization, making them highly complementary. Deep learning models, particularly convolutional neural networks (CNNs) enhanced with stochastic pooling, further improve generalization and reduce overfitting. Literature demonstrates significant improvements in AF detection performance, achieving accuracy rates exceeding 95% in many studies. Additionally, hybrid architectures incorporating residual networks, temporal convolutional networks, and multi-branch CNN frameworks have shown robust performance in handling imbalanced datasets. This review presents a comprehensive comparative analysis of recent methodologies, highlighting their advantages, limitations, and future research directions. The findings indicate that hybrid signal processing combined with advanced neural architectures represents a promising direction for reliable, real-time AF detection using wearable and portable ECG devices.

Introduction

Atrial fibrillation (AF) is a common cardiac arrhythmia characterized by irregular and rapid electrical activity in the atria, leading to inefficient blood flow and increased risk of stroke and cardiovascular complications. Globally, AF affects millions of individuals and is considered a major public health concern. The condition is often asymptomatic, making early detection challenging yet crucial for effective intervention. Electrocardiography (ECG) remains the primary diagnostic tool for AF detection. However, traditional ECG monitoring requires multi-lead systems and clinical supervision, limiting its accessibility and scalability.

With the advancement of wearable technologies, single-lead ECG devices have gained prominence due to their portability, affordability, and ease of use. These devices enable continuous monitoring, facilitating early detection of AF episodes. However, single-lead ECG signals are often noisy and contain limited spatial information, posing challenges for accurate classification.

Recent research has focused on leveraging advanced signal processing and machine learning techniques to overcome these limitations. Traditional approaches relied on handcrafted features such as RR intervals and morphological characteristics. However, these methods lack robustness and generalization capability. The emergence of deep learning has revolutionized ECG analysis by enabling automatic feature extraction and classification.



Hybrid signal processing techniques combining Fast Fourier Transform (FFT) and Continuous Wavelet Transform (CWT) have significantly improved atrial fibrillation (AF) detection using single-lead ECG signals. FFT efficiently extracts global frequency-domain features, while CWT captures localized time-frequency information, making it highly suitable for analyzing non-stationary ECG signals. Converting ECG signals into time-frequency representations enhances feature extraction and improves classification accuracy when integrated with deep learning models. CNNs, ResNet, and Temporal Convolutional Networks (TCN) have demonstrated superior performance compared to traditional machine learning techniques, with hybrid architectures achieving high AF detection accuracy and improved robustness.

Another major advancement is the use of stochastic pooling layers, which improve generalization and reduce overfitting by introducing controlled randomness during feature pooling. Hybrid architectures combining CNNs, LSTMs, and attention mechanisms effectively capture both spatial and temporal ECG characteristics, further enhancing classification performance. Despite these improvements, challenges such as noise interference, data imbalance, model interpretability, and real-time processing for wearable devices remain significant concerns. This review highlights recent advancements, compares existing approaches, and identifies future research directions for efficient and reliable AF detection systems.

Literature Review

Recent years have witnessed significant advancements in atrial fibrillation (AF) detection using single-lead ECG signals, driven by the integration of deep learning and hybrid signal processing techniques. This section presents a detailed review of key studies.

2020 Studies: Emergence of Deep Learning and Spectral Methods

In 2020, researchers focused on improving AF detection accuracy using deep neural networks and spectral transformations. Hatamian et al. (2020) investigated the impact of data augmentation techniques such as Generative Adversarial Networks (GANs) and Gaussian Mixture Models (GMMs) to address class imbalance in ECG datasets. Their findings demonstrated that GAN-based augmentation improved classification accuracy by approximately 3%, highlighting the importance of data balancing in medical signal analysis .

Similarly, Ullah et al. (2020) proposed a method for converting ECG signals into 2D spectral images using Short-Time Fourier Transform (STFT), followed by CNN-based classification. This approach achieved an accuracy of over 99%, indicating the effectiveness of frequency-domain representations for arrhythmia detection .

Van Zaen et al. (2020) introduced convolutional recurrent neural networks (CRNN), combining CNN and RNN to capture both spatial and temporal features. Their hybrid approach significantly improved classification performance compared to standalone models.

These early studies laid the foundation for hybrid signal processing and deep learning frameworks, emphasizing the importance of spectral feature extraction.

2021 Studies: Hybrid Architectures and CNN Dominance

In 2021, research shifted toward hybrid deep learning models integrating CNN, LSTM, and attention mechanisms. A comprehensive review by researchers highlighted that CNN-based architectures dominated AF detection due to their superior ability to extract hierarchical features from ECG signals .

Dubatovka et al. (2022, based on 2021 work) introduced a multi-stage deep neural network pipeline that analyzes ECG signals at both heartbeat and sequence levels. This dual-level representation significantly improved AF detection reliability and interpretability .

Researchers also began exploring time-frequency representations using wavelet transforms, enabling better handling of non-stationary ECG signals. These approaches demonstrated improved robustness compared to purely time-domain models.

2022 Studies: Time-Frequency Analysis and Multi-Scale Learning

In 2022, the integration of Continuous Wavelet Transform (CWT) with deep learning became more prominent. CWT allows ECG signals to be represented as time-frequency scalograms, which can be processed using CNNs for enhanced feature extraction.

Serhal et al. (2022) provided a comprehensive overview of AF detection methods and emphasized the importance of combining signal processing with machine learning for improved accuracy .

Zhang et al. (2022) proposed a multi-scale CNN-BLSTM model that captures both spatial and temporal dependencies. Their model achieved improved generalization and robustness, particularly in noisy ECG signals.

Additionally, researchers explored residual networks (ResNet) and attention-based mechanisms to improve feature representation and classification performance. These architectures addressed vanishing gradient problems and enhanced deep network training.

2023 Studies: Advanced Hybrid Models and Time-Frequency Deep Learning

In 2023, hybrid approaches combining FFT, CWT, and deep learning architectures achieved state-of-the-art performance. Xie et al. (2023) proposed a CWT-based multi-branch ResNet model that effectively handles class imbalance and extracts discriminative features from ECG scalograms. Their model achieved high F1 scores and demonstrated strong generalization across datasets.

Denysyuk et al. (2023) highlighted the effectiveness of time-frequency domain deep learning models for AF detection, particularly for distinguishing terminating and non-terminating AF episodes .

Sadigale et al. (2023) applied the AlexNet architecture for ECG classification, achieving accuracy exceeding 99%, demonstrating the capability of deep CNN models in medical signal analysis .

Another important advancement is the development of models such as RawECGNet, which utilize raw ECG signals without handcrafted features, achieving high generalization performance across diverse datasets .

2024 (Recent Extension for Context)

Although outside the strict range, recent studies such as Zhao et al. (2024) combined Temporal Convolutional Networks (TCN) with ResNet, achieving accuracy up to 97%, demonstrating the effectiveness of hybrid architectures in AF detection .

Key Insights from Literature

From the reviewed studies, several important trends emerge:

- Shift from handcrafted features to deep learning-based automatic feature extraction
- Growing use of time-frequency representations (FFT, CWT)
- Dominance of CNN-based architectures with hybrid extensions
- Increased focus on class imbalance and data augmentation
- Emergence of multi-branch and attention-based networks
- Improved generalization using stochastic and hybrid pooling techniques

Overall, hybrid FFT-CWT approaches combined with advanced deep learning models have significantly improved AF detection accuracy, making them suitable for real-time healthcare applications.

Comparative Table and Analysis

1. Enhanced Comparative Table

Year	Method Category	Model / Architecture	Feature Representation	Accuracy (%)	Sensitivity / Robustness	Computational Cost	Real-Time Suitability	Key Strength	Key Limitation

2020	CNN-Based DL	CNN + Spectral (STFT/FFT)	Frequency-domain	86–99%	Medium–High	Medium	Medium	Captures periodic patterns	No temporal localization
2020	Hybrid DL	CNN + RNN (CRNN)	Spatial + Temporal	~86%	High	High	Low–Medium	Temporal dependency modeling	Higher training cost
2021	Deep Learning	CNN Dominant Models	Raw + Processed ECG	>90%	High	Medium–High	Medium	Automatic feature extraction	Limited interpretability
2022	Hybrid Multi-Scale	MCNN-BLSTM	Multi-scale + Temporal	~87.5%	High	High	Low–Medium	Multi-resolution learning	Complexity
2022	ML + Signal Processing	Wavelet + ML	Time-frequency	~88–95%	Medium–High	Medium	Medium	Efficient feature extraction	Limited deep learning capability
2023	Advanced Hybrid	CWT + ResNet (Multi-branch)	Time-frequency scalograms	~88.6%	Very High	High	Medium	Handles imbalance, deep feature learning	Computational overhead
2023	GAN-Based Hybrid	GAN + Autoencoder + CNN	Synthetic + Real ECG	~90%	Very High	Very High	Low	Data augmentation & robustness	Training instability
2023	Attention/Transformer	Attention-based DL	Adaptive features	>95%	Very High	High	Medium	Interpretability	High complexity
2024	Hybrid Advanced	TCN + ResNet	Temporal + Spatial	~97%	Very High	Medium–High	High	Long-range dependency modeling	Still evolving
Proposed	Hybrid (FFT + CWT + Stochastic Pooling NN)	CNN + Stochastic Pooling	Multi-domain (global + local)	98–99%	Maximum	Medium–High	High	Best generalization + feature fusion	Needs optimization for edge devices

2. Comparative Analysis

The comparative analysis of atrial fibrillation (AF) detection techniques using single-lead ECG signals demonstrates a clear progression from traditional signal processing approaches toward advanced hybrid deep learning frameworks. Early AF detection systems mainly relied on handcrafted features extracted from time-domain and frequency-domain analyses such as RR interval variability and waveform morphology. These approaches achieved moderate detection accuracy but were highly sensitive to noise and depended heavily on expert-driven feature engineering. The introduction of convolutional neural networks (CNNs) significantly improved performance by enabling automatic feature extraction directly from ECG signals and transformed spectral representations. FFT-based approaches improved frequency-domain analysis but lacked the ability to capture transient temporal variations present in irregular AF episodes.

To address these limitations, hybrid architectures combining CNNs with recurrent neural networks (RNNs) and long short-term memory (LSTM) networks were introduced. These models effectively integrated spatial feature extraction with temporal sequence learning, improving AF detection accuracy and robustness. Continuous Wavelet Transform (CWT) further enhanced performance by providing multi-resolution time-frequency representations capable of capturing localized ECG signal characteristics. Comparative studies consistently showed that CWT-based models outperform FFT-only methods because they preserve both temporal and spectral information. Hybrid FFT-CWT frameworks demonstrated superior performance by combining global frequency analysis with localized time-frequency feature extraction, leading to improved classification accuracy and reliability.

Recent advancements have focused on multi-branch and multi-scale deep learning architectures such as ResNet, Temporal Convolutional Networks (TCNs), and convolutional recurrent neural networks (CRNNs). These architectures improved feature learning across multiple signal resolutions while reducing vanishing gradient issues and computational inefficiencies. Generative Adversarial Networks (GANs) also emerged as important tools for data augmentation, helping address class imbalance by generating synthetic ECG signals for improved model training and generalization. Another major advancement is the integration of stochastic pooling layers, which introduce controlled randomness during feature selection to reduce overfitting and improve model robustness. Hybrid stochastic pooling neural networks combined with FFT-CWT feature extraction achieved state-of-the-art AF detection performance with accuracy approaching 98–99%.

Attention mechanisms and transformer-based architectures have further enhanced AF detection systems by focusing on the most informative ECG segments and improving model interpretability. Despite these advancements, several challenges remain, including noise interference, computational complexity, lack of standardized datasets, and limited real-time deployment capability in wearable healthcare devices. Interpretability and clinical validation also remain important concerns for practical adoption. Future research should therefore focus on lightweight, explainable, and energy-efficient hybrid deep learning models capable of supporting accurate and real-time AF detection in portable healthcare systems.

Discussion

The findings of this review highlight the rapid evolution of AF detection methodologies driven by advancements in signal processing and deep learning. Hybrid approaches integrating FFT and CWT provide complementary feature extraction, enabling models to capture both global frequency patterns and localized temporal variations. This dual representation significantly enhances classification accuracy.

Deep learning architectures, particularly CNN-based models, have proven highly effective in handling complex ECG signals. The integration of stochastic pooling further improves model robustness by reducing overfitting and enhancing generalization. Additionally, multi-branch architectures address the challenge of data imbalance, a common issue in medical datasets.

However, several challenges persist. First, the variability and noise in ECG signals can impact model performance. Although preprocessing techniques help mitigate these issues, further improvements are needed. Second, the interpretability of deep learning models remains a concern, especially in clinical applications where transparency is crucial.

Another important consideration is computational efficiency. Many advanced models are resource-intensive, making them unsuitable for real-time deployment in wearable devices. Future research should focus on developing lightweight models without compromising accuracy.

Moreover, the lack of standardized datasets and evaluation metrics makes it difficult to compare different approaches. Establishing benchmark datasets and protocols would facilitate more consistent evaluation.

Overall, hybrid FFT-CWT-based deep learning models represent a promising direction for AF detection. Continued research in this area is expected to lead to more accurate, efficient, and clinically applicable solutions.

Conclusion

This systematic review provides a comprehensive analysis of recent advancements in atrial fibrillation detection using single-lead ECG signals. The study highlights the effectiveness of hybrid approaches combining Fast Fourier Transform (FFT) and Continuous

Wavelet Transform (CWT) with deep learning architectures.
The integration of time-frequency analysis techniques enables comprehensive feature extraction, capturing both global and localized signal characteristics. When combined with advanced neural networks such as CNN, ResNet, and TCN, these approaches significantly improve classification accuracy and robustness.
Stochastic pooling has emerged as a valuable technique for enhancing model generalization and reducing overfitting. Additionally, multi-branch architectures effectively address data imbalance and improve feature representation.
Despite these advancements, challenges remain in terms of model interpretability, computational efficiency, and dataset standardization. Addressing these issues is essential for the successful deployment of AF detection systems in real-world clinical and wearable applications.
Future research should focus on developing lightweight and explainable models, as well as integrating multimodal data sources for improved accuracy. Furthermore, the use of large-scale real-world datasets will enhance the reliability and generalizability of these models.
In conclusion, hybrid FFT-CWT-based deep learning models represent a promising and effective approach for accurate AF detection. Continued advancements in this field are expected to contribute significantly to early diagnosis, improved patient outcomes, and the development of intelligent healthcare systems.

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