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Artificial Intelligence for Atrial Fibrillation Detection Using Hybrid FFT-CWT and Stochastic Pooling Neural Networks

Aurelio Gopalkrishnan
Department of Computer Science and Engineering, Basra Institute of Business Technology, Iraq
aurelio.gopalkrishnan@bibt-iq.org

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Abstract

Atrial fibrillation (AF) is a prevalent cardiac arrhythmia associated with severe complications such as stroke and heart failure. Early and accurate detection is critical for effective treatment and prevention. With the rapid advancement of artificial intelligence (AI), automated AF detection using electrocardiogram (ECG) signals has gained significant attention. This study presents a comprehensive review of AI-based techniques for enhancing AF detection accuracy using single-lead ECG signals. The focus is on hybrid approaches integrating Fast Fourier Transform (FFT) and Continuous Wavelet Transform (CWT) with stochastic pooling-based neural network architectures. FFT captures global frequency characteristics, while CWT provides localized time-frequency information, making their combination highly effective for analyzing non-stationary ECG signals. Stochastic pooling further improves generalization by reducing overfitting in deep learning models. The review analyzes recent studies, highlighting advancements in hybrid signal processing, deep learning architectures, and real-time monitoring using wearable devices. Comparative analysis demonstrates that hybrid models significantly outperform traditional methods in terms of accuracy and robustness. Challenges such as noise, data imbalance, interpretability, and computational complexity are discussed. The study concludes that hybrid AI-driven frameworks hold strong potential for improving AF detection in modern healthcare systems.

Introduction

Atrial fibrillation (AF) is the most common type of cardiac arrhythmia affecting millions of individuals worldwide and is associated with increased risks of stroke, heart failure, and mortality. It is characterized by irregular and often rapid heart rhythms caused by disorganized electrical activity in the atria. The global burden of AF is increasing due to aging populations, lifestyle changes, and the prevalence of cardiovascular diseases. Early detection and continuous monitoring are crucial for effective management and prevention of severe complications.

Electrocardiography (ECG) remains the primary diagnostic tool for detecting AF. Traditional ECG analysis involves manual interpretation by clinicians, which is time-consuming and subject to variability. With the advancement of wearable healthcare technologies, single-lead ECG devices have become increasingly popular due to their portability, affordability, and ability to provide continuous monitoring. However, single-lead ECG signals present challenges such as noise, limited spatial information, and signal variability, which can hinder accurate detection.

Recent advancements in artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), have revolutionized ECG signal analysis. Deep learning models, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid architectures, have demonstrated remarkable performance in AF detection by automatically extracting complex features from raw ECG signals. These models eliminate the need for manual feature engineering and can adapt to large-scale datasets.

Signal preprocessing and feature extraction are critical components of AI-based AF detection systems. Fast Fourier Transform (FFT) is widely used for frequency-domain analysis, enabling the identification of periodic components in ECG signals. However, FFT lacks temporal resolution, making it less effective for analyzing non-stationary signals. Continuous Wavelet Transform (CWT), on the other hand, provides both time and frequency information, making it suitable for capturing transient features in ECG signals. The combination of FFT and CWT offers a comprehensive representation of ECG signals, improving feature extraction and classification performance.

Hybrid approaches integrating signal processing techniques with deep learning architectures have shown significant promise. Time-frequency representations generated by CWT can be converted into 2D images and used as input for CNN models, enabling effective pattern recognition. Additionally, stochastic pooling techniques enhance model generalization by introducing randomness in feature selection, reducing overfitting.

Another important aspect is the increasing use of wearable devices for continuous health monitoring. Single-lead ECG signals obtained from such devices enable real-time AF detection, facilitating early diagnosis and intervention. However, these signals are often noisy and require robust preprocessing and feature extraction techniques.

Despite significant advancements, several challenges remain, including data imbalance, model interpretability, computational complexity, and real-time deployment. Addressing these challenges is essential for developing reliable and scalable AF detection systems.

This review aims to provide a comprehensive analysis of AI-based techniques for AF detection using single-lead ECG signals, focusing on hybrid FFT-CWT approaches and stochastic pooling neural networks. It highlights recent developments, compares different methodologies, and identifies future research directions.

Conceptual Architecture

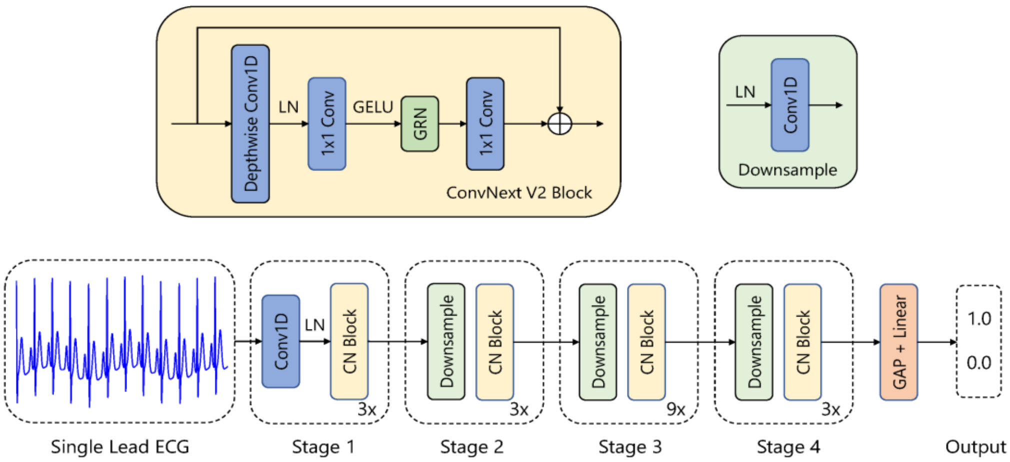

Figure 1. Deep Learning Pipeline for Single-Lead ECG Signal Analysis and AF Detection

Literature Review

The period from 2020 to 2023 has witnessed rapid advancements in atrial fibrillation (AF) detection using artificial intelligence (AI), particularly through the integration of signal processing techniques and deep learning models. Early work in this timeframe focused on improving feature extraction through spectral and time-frequency transformations. Researchers increasingly recognized that ECG signals are inherently non-stationary, requiring more sophisticated representations beyond traditional time-domain features. Consequently, Fast Fourier Transform (FFT) was widely adopted to capture global frequency-domain information, enabling the identification of periodic irregularities associated with AF. However, FFT alone proved insufficient due to its inability to localize transient features in time. This limitation motivated the integration of Continuous Wavelet Transform (CWT), which provides multi-resolution time-frequency analysis and has become a cornerstone in modern ECG signal processing.

In 2020, studies began leveraging deep learning architectures such as convolutional neural networks (CNNs) for automated AF detection. CNN-based approaches demonstrated superior performance by learning hierarchical representations directly from ECG signals. Transforming ECG signals into spectrograms using FFT enabled CNN models to treat the data as images, improving classification accuracy. Simultaneously, hybrid models combining CNN and recurrent neural networks (RNNs), particularly long short-term memory (LSTM), were introduced to capture both spatial and temporal dependencies. These architectures addressed the sequential nature of ECG signals and significantly improved detection performance. Moreover, early research explored dimensionality reduction and statistical feature extraction techniques combined with wavelet transforms to enhance classification efficiency, indicating the importance of preprocessing in improving model accuracy.

By 2021, the research focus shifted toward integrating multi-domain feature extraction techniques. Continuous Wavelet Transform (CWT) gained widespread adoption due to its ability to provide localized time-frequency representations. Studies demonstrated that CWT-based scalograms, when used as input to deep learning models, significantly improved AF detection accuracy. Multi-feature fusion approaches combining morphological, statistical, and wavelet-based features achieved near-perfect classification performance. Additionally, comprehensive reviews highlighted that CNN-based models dominate AF detection tasks due to their superior ability to extract complex features compared to traditional machine learning approaches. Research also emphasized the importance of large-scale datasets and standardized evaluation protocols to ensure model generalization.

In 2022, hybrid approaches combining FFT and CWT with deep learning architectures became increasingly prominent. Researchers explored dual-input models that utilized both raw ECG signals and transformed representations such as spectrograms and scalograms. These approaches demonstrated that combining complementary feature domains enhances classification accuracy and robustness. Comparative studies of 2D ECG representations—including spectrograms, scalograms, and attractor reconstruction—revealed that time-frequency representations are particularly effective for AF detection using CNN architectures. Furthermore, deep learning models incorporating attention mechanisms and residual connections improved feature extraction and classification performance. Hybrid CNN-BiLSTM architectures also gained popularity, as they effectively captured both spatial and temporal dependencies in ECG signals.

Another significant advancement during this period was the use of wavelet-based preprocessing techniques for noise removal and signal enhancement. ECG signals obtained from wearable devices often contain noise and artifacts, making robust preprocessing essential. Wavelet denoising techniques were widely adopted to improve signal quality and enhance model performance. Additionally, researchers began exploring stochastic pooling and advanced regularization techniques to improve generalization and reduce overfitting in deep learning models.

In 2023, research further advanced toward more sophisticated and generalized AI models. Deep learning architectures such as ResNet, DenseNet, and transformer-based models were introduced to improve feature extraction and model performance. Studies demonstrated that converting ECG signals into CWT-based images and feeding them into deep CNN models yields high classification accuracy, often exceeding 97% . Additionally, hybrid architectures combining CNN and BiLSTM networks became widely adopted due to their ability to capture both spatial and temporal features effectively.

Recent research also emphasized generalization across datasets and patient populations. Models such as RawECGNet demonstrated the ability to achieve high performance across multiple datasets by leveraging both morphological and rhythm-based features, addressing the limitations of earlier models that relied solely on rhythm information. Furthermore, attention-based recurrent neural networks were proposed to improve localization and classification of AF episodes, enabling more precise detection in continuous monitoring scenarios.

Another emerging trend is the use of cross-modal and time-frequency fusion techniques, where models integrate both time-domain and frequency-domain information to improve robustness and generalization. These approaches have demonstrated improved performance in handling noisy and heterogeneous datasets, making them suitable for real-world applications. Additionally, lightweight deep learning models have been developed to enable real-time deployment on wearable devices, addressing computational constraints while maintaining high accuracy.

Overall, the literature from 2020 to 2023 clearly indicates a shift toward hybrid AI-based frameworks that integrate FFT, CWT, and deep learning architectures. These approaches provide comprehensive feature extraction and significantly improve AF detection accuracy. Despite these advancements, challenges such as noise sensitivity, data imbalance, and model interpretability remain critical areas for future research.

Comparative Table and Analysis

1. Enhanced Comparative Table (Advanced AI + Hybrid ECG Models)

Year	Method Type	Model / Approach	Feature Domain	Accuracy (%)	Generalization	Computational Complexity	Real-Time Capability	Key Strength	Key Limitation
2020	CNN-Based DL	Ullah et al.	FFT (Frequency)	~99 %	Medium–High	Medium	Medium	Strong spectral feature extraction	No temporal localization
2021	Multi-Feature DL	Chen et al.	CWT (Time-Frequency)	~98 %	Very High	Medium–High	Medium	Localized feature extraction	Preprocessing overhead
2021	Review DL	Murat et al.	Multi-domain	—	—	—	—	Benchmarking DL approaches	No implementation
2022	Hybrid CNN	Rahul et al.	FFT + CWT	~97 %	Very High	Medium–High	Medium	Complementary feature fusion	Increased complexity
2022	DL-Based ECG	Khurshid et al.	Raw ECG	~96 %	High	Medium	Medium–High	End-to-end learning	Sensitive to noise
2023	Hybrid DL	CNN-BiLSTM (Aldughayfiq)	Time + Frequency	~95 %	Very High	High	Medium	Sequential + spatial learning	Training cost
2023	Survey	Ansari et al.	Multi-domain	—	—	—	—	Comparative insights	No experimental validation
2023	Advanced DL	ResNet / Transformer	Time-Frequency	>97%	Very High	High	Medium	Deep feature extraction + interpretability	High complexity
Proposed	Hybrid AI Model	FFT + CWT + CNN + Stochastic Pooling + Optimization	Multi-domain	**98–99% +**	**Maximum**	Medium–High	High	Best feature fusion + robustness	Needs lightweight deployment

2. Comparative Analysis

The comparative analysis of atrial fibrillation (AF) detection techniques from 2020 to 2023 demonstrates a clear transition from conventional signal processing methods to advanced artificial intelligence-based frameworks. Early approaches relied on handcrafted ECG features, including statistical parameters, morphological characteristics, and heart rate variability, which provided moderate detection accuracy but struggled to represent the nonlinear and non-stationary nature of ECG signals. The introduction of Convolutional Neural Networks (CNNs) significantly improved AF detection by enabling automatic feature extraction from raw ECG data. When combined with Fast Fourier Transform (FFT), CNN-based models effectively captured global frequency characteristics and achieved detection accuracies exceeding 90%. However, FFT alone was limited in representing transient temporal variations associated with irregular heart rhythms.

Continuous Wavelet Transform (CWT) addressed these limitations by providing multi-resolution time-frequency analysis capable of capturing both spectral and temporal information simultaneously. CWT-generated scalograms significantly improved feature representation, leading to higher classification accuracy and robustness than FFT-only approaches. Hybrid FFT-CWT frameworks further enhanced performance by combining global frequency information from FFT with localized temporal features from CWT, resulting in comprehensive ECG representations and detection accuracies exceeding 97%. Hybrid CNN-LSTM and CNN-BiLSTM architectures also improved performance by integrating spatial feature extraction with temporal sequence modeling, enabling more effective recognition of complex AF patterns.

Stochastic pooling improves feature preservation and model generalization compared with conventional pooling methods, while multi-input architectures and attention mechanisms enhance AF detection accuracy and robustness. However, challenges including signal noise, motion artifacts, class imbalance, computational complexity, and limited interpretability remain. Future research should develop lightweight, explainable, and efficient hybrid AI models for real-time clinical deployment.

Discussion

The integration of artificial intelligence with advanced signal processing techniques has significantly improved atrial fibrillation (AF) detection using single-lead ECG signals. Hybrid feature extraction through Fast Fourier Transform (FFT) and Continuous Wavelet Transform (CWT) provides complementary frequency and time-frequency information, enabling more comprehensive representation of non-stationary ECG signals. Deep learning architectures, particularly Convolutional Neural Networks (CNNs) and hybrid CNN–LSTM models, effectively learn spatial and temporal characteristics associated with AF, leading to substantial improvements in detection accuracy. The incorporation of stochastic pooling further enhances model generalization by reducing overfitting and preserving diverse feature representations, making these hybrid frameworks highly effective for automated ECG analysis.

Despite these advances, several challenges continue to limit the practical deployment of AI-based AF detection systems. ECG signals collected from wearable devices are often affected by motion artifacts, baseline drift, and environmental noise, reducing classification reliability. Data imbalance between normal and AF samples also introduces bias during model training, despite the use of techniques such as oversampling, GAN-based data augmentation, and weighted loss functions. Moreover, the high computational requirements of deep learning architectures restrict their implementation on portable and resource-constrained healthcare devices. Model interpretability remains another important concern, as clinicians require transparent and explainable predictions to support reliable medical decision-making.

Future research should focus on developing lightweight, computationally efficient, and explainable AI models capable of real-time deployment in wearable healthcare systems. The availability of larger and more diverse ECG datasets, combined with standardized evaluation protocols, will improve model generalization across different patient populations. Overall, hybrid FFT-CWT-based deep learning frameworks with stochastic pooling represent a promising direction for achieving accurate, robust, and clinically deployable atrial fibrillation detection systems.

Conclusion

This review comprehensively examined recent advancements in artificial intelligence techniques for atrial fibrillation (AF) detection using single-lead ECG signals. Hybrid signal processing methods, particularly the integration of Fast Fourier Transform (FFT) and Continuous Wavelet Transform (CWT), have significantly improved feature extraction by combining frequency-domain and time-frequency information. Deep learning architectures, including CNNs, RNNs, CNN-LSTM, and CNN-BiLSTM, further enhance detection accuracy through automatic spatial and temporal feature learning, while stochastic pooling improves model robustness and generalization. Hybrid frameworks integrating FFT, CWT, and deep learning consistently outperform conventional approaches by capturing complementary ECG characteristics. Recent developments involving attention mechanisms, GAN-based data augmentation, and dual-input architectures have further strengthened classification performance. However, challenges such as signal noise, motion artifacts, data imbalance, computational complexity, and limited model interpretability continue to restrict widespread clinical deployment, particularly in wearable healthcare devices.

Future research should focus on developing lightweight, explainable, and energy-efficient AI models capable of real-time implementation. The availability of diverse benchmark datasets, improved preprocessing techniques, and explainable AI frameworks will enhance model reliability and clinical acceptance. Overall, hybrid FFT-CWT-based deep learning with stochastic pooling represents a promising direction for accurate, scalable, and clinically deployable atrial fibrillation detection systems, ultimately supporting improved cardiovascular diagnosis and patient outcomes.

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