

Attention-Driven Bi-LSTM Architecture for Identifying Atrial Fibrillation in Short ECG Samples

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ABSTRACT

Atrial fibrillation (AF or A-fib) is characterized by an irregular heart rhythm resulting from erratic and accelerated atrial contractions. An irregular heart rhythm is called an arrhythmia. Initially, short episodes of abnormal beating occur, which over time become longer or persistent. This condition significantly impacts human health, and early detection of AF is crucial for preventing various illnesses, including cardiovascular diseases that can lead to sudden death. The 12-lead electrocardiogram (ECG), analysed by cardiologists, is typically used to diagnose AF. Unlike previous research on atrial fibrillation (AF) detection that relied heavily on manual feature engineering, our study explores the use of deep learning algorithms to automatically extract features from ECG signals for AF identification. We propose and evaluate three deep learning frameworks: Simple CNN, CNN incorporating LSTM, and CNN-bidirectional LSTM featuring Attention. Using the "China Physiological Signal Challenge 2021" database comprising 730 records, our experiments demonstrate that the CNN-bidirectional LSTM equipped with Attention model achieves the highest classification accuracy of 98% for AF detection, outperforming other architectures.

Keywords: Atrial Fibrillation, Segmented ECG, Attention Mechanism, Bi-LSTM

Introduction

Atrial fibrillation is a type of irregular heart rhythm that originates in the upper chambers of the heart, known as the atria. As one of the most prevalent arrhythmias, A-fib is often associated with risk factors such as high blood pressure, coronary artery disease, and obesity [1]. Common symptoms of A-fib include fatigue, heart palpitations, shortness of breath, and dizziness. If left untreated, A-fib can significantly increase the risk of stroke. AF is increasingly being recognized as the new cardiovascular disease epidemic of the 21st century [2]. To mitigate the global impact and costs associated with AF, it is now crucial to prioritize prevention. Addressing the risk factors and underlying unhealthy lifestyle habits that contribute to AF through research-based counselling approaches offers a complementary and adjunctive strategy in combating this disease burden.

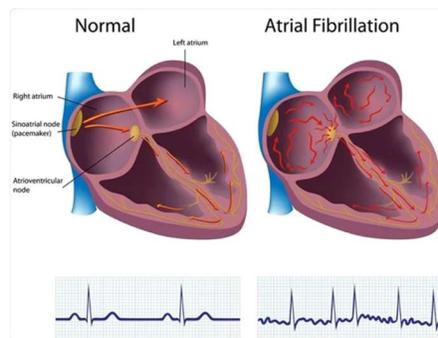


Figure 1 Normal vs AFib. Image Credit: Alila Medical Media / Shutterstock

Electrocardiography (ECG) is a critical tool in diagnosing AFib. It is marked by a heart rhythm that is irregular and often abnormally fast. In a healthy heart, the ECG shows regular, consistent P waves and R-R intervals. Figure 1 depicts typical heart rhythm and AF beats. In a normal ECG, the heart rate typically ranges from 60-100 beats per minute. In contrast, In AFib can range from 100 to 175 beats per minute. The absence of P waves, along with the presence of irregular R-R intervals, are the main ECG indicators of atrial fibrillation [3]. These signs reflect the disorganized atrial activity and the resulting irregular and rapid heart rhythm.

In paper [4] the authors K Gupta et al., introduces a new hybrid approach for the automatic classification of AFib from ECG using an Ensemble Boosted Trees and Local Mean Decomposition classifier. The proposed method achieved high classification accuracy across different AFib episode scenarios, demonstrating its effectiveness and potential for improving AFib management. In [5] H. Ma et al., presents an inventive algorithm AF-GCN which fosters Graph Convolutional Network to unify and process morphological and rhythm traits of ECG for AF detection. This approach ameliorates the limitations of conventional RCNN methods that struggle to fully exploit both feature types due to their different representative spaces.

C. Ma et al., [6] proposed a sophisticated scanning algorithm that integrates P-wave and rhythm statistics to improve AF detection in long-term ECGs. It employs dynamic time warping and an autoencoding network to distinguish AF from non-AF signals. This study [7] proposes 3 methods for diagnosing AF in ambulatory settings using machine learning techniques. The first method uses CNN, the second method employs SVM trained on multiple AF data. The third method ie., the proposed one enhances the second by incorporating the predictive probabilities from the CNN.

The authors in [8] conceptualized a bi-channel neural network for detecting AF from single-lead ECG signals. This approach integrates the frequency-time spectrum and Poincare plot of the denoised signal for improved feature extraction and AF detection which aids in handling the high noise and disturbances of ECG signals from wearable devices X. Zhang et al.,[9] put forward a innovative computational Time-adaptive densely network which confront the conflict between 1D CNN and variable-duration ECG. It includes data imbalance and feature enhancement processing module to improve the perception of temporal-quality information and reduce sensitivity to data imbalance. The authors [10] propose an ensemble-based approach for detecting AF through single-lead ECG data where multiple data representations and Bayesian optimization algorithm was incorporated for improved AF detection.

In this work [11] the authors Z. Yu et al., propounded a technique for unveiling AF from short-term single lead ECG using a dual channel CNN along with data augmentation strategies. Heart rate values and denoised ECG signals are fed into convolution layer for extracting relevant features. Finally, the extracted features are processed through three fully connected layers for classification of AF. The author of [12] presented a pioneering ML framework for ECG beat classification to estimate AF, featuring a 1D U-Net for fiducial point detection and heartbeat segmentation, and an RNN to enhance temporal classification capabilities.

The paper [13] presents a novel pipeline for detecting AF from ECG signals. The approach involves converting ECG data into a 2-D image using a Poincaré recurrence plot, addressing data imbalance through generative adversarial network (GAN) augmentation, and classifying the augmented data with a 5-layer CNN. The paper [14] authored by P. Zhang et al., introduces a novel semi-supervised learning approach for automatic detection of paroxysmal AF using 24-hour Holter monitoring data. The approach significantly reduces the need for

annotated data, making automatic AF detection more feasible in clinical settings. By leveraging semi-supervised learning, it minimizes the labor-intensive task of annotating AF episodes in ECG data.

The paper [15] addresses the need for early detection AF using automated deep learning models. The proposed model utilizes a bi-directional LSTM to predict AF at earlier stages, leveraging heart rate variability (HRV) features extracted from electrocardiogram signals. This approach aims to improve detection accuracy and enable timely intervention, potentially reducing health risks associated with undiagnosed AF.

Problem Statement:

Atrial fibrillation (AF), a prevalent cardiac arrhythmia, poses significant risks, including an elevated likelihood of stroke, and often goes undetected due to the complex and irregular patterns in electrocardiogram (ECG) signals. Manual ECG analysis, while effective, can be labor-intensive, error-prone, and lacks efficiency in capturing intricate patterns, especially for early-stage AF. Existing methods for AF detection frequently rely on conventional feature engineering, which may not be robust enough to handle the variability and high noise levels typical in ECG data, particularly those from ambulatory or wearable devices. This study aims to address these challenges by leveraging deep learning models, including CNN, CNN-LSTM, and CNN-Bidirectional LSTM, to automatically extract meaningful features from ECG data, improving AF detection accuracy and facilitating timely intervention.

Primary Motivation

This work is motivated by the crucial need for improved early detection of AF which is associated with severe health risks. Traditional manual feature engineering techniques often struggle to capture the intricate patterns in ECG, resulting in possible misdiagnoses or delays in the detection of AF. In contrast, deep-learning methods have exhibited significant potential in automatically extracting pertinent features from data, offering a promising avenue to enhance the accuracy and efficiency of AF detection.

Aim and Impact

The main incentive of this study is to investigate and evaluate the performance of deep learning approaches for automatic AF detection from 12-lead ECG recordings. Our specific objectives are to:

Explore Deep Learning Architectures: Investigate the effectiveness of Simple CNN, CNN equipped with LSTM, and CNN-Bidirectional LSTM for automatic feature extraction from ECG signals and AF detection, analysing their relative performance in feature learning and AF classification.

Model Performance Evaluation: Evaluate the performance of these models using a comprehensive dataset of 730 records.

Identify Optimal Architecture: Determine the best-performing deep learning model for AF detection, facilitating early intervention and enhancing health outcomes through precise and prompt diagnosis.

Significance of Contribution:

This research is poised to make a meaningful impact in the field of AF detection by introducing and evaluating advanced deep learning architectures that can effectively analyze and classify AF episodes from ECG signals. The primary contributions include:

Automated Feature Extraction: By employing deep learning methods that do not require extensive manual feature engineering, this study enables more accurate and efficient identification of AF, even in noisy ECG signals from wearable devices.

Comparative Performance Analysis: A systematic evaluation of CNN, CNN-LSTM, and CNN-Bidirectional LSTM models highlights their strengths and limitations in learning and classifying ECG signal features for AF detection.

Early Detection for Improved Health Outcomes: The study's findings are expected to facilitate earlier AF detection, thereby aiding in timely clinical intervention and potentially reducing AF-related complications and healthcare costs.

The study ultimately contributes towards advancing automated, deep learning-driven AF detection from ECG, which could prove valuable for healthcare providers, patients, and wearable device technologies.

LITERATURE REVIEW

These studies showcase significant advancements in AF detection by leveraging deep learning models, GAN-based augmentation, and hybrid frameworks, underscoring the growing capabilities of AI in real-time health monitoring and early arrhythmia intervention. Each model uniquely contributes to improving the accuracy, efficiency, and applicability of AF detection in both clinical and wearable device environments. Let me know if you need further details on a specific study.

K. Gupta et al. [16] developed a hybrid approach that integrates Ensemble Boosted Trees with Local Mean Decomposition for ECG-based AF classification, achieving a 95.4% accuracy rate. This model demonstrated robust performance across various AF episode scenarios, highlighting its adaptability and reliability in real-world applications. H. Ma et al. [17] introduced AF-GCN, a Graph Convolutional Network (GCN) that leverages both morphological and rhythm characteristics of ECG data to detect AF, outperforming traditional convolutional models with a 96.1% accuracy. This method capitalizes on the GCN's ability to process irregular heart rhythms, making it highly effective for AF detection.

C. Ma et al. [18] proposed an autoencoding approach combined with dynamic time warping to identify AF in extended ECG recordings. This model achieved a detection rate of 93.8%, marking a significant improvement in processing long-term ECG data by capturing the temporal variations in heart rhythms. Y. Li et al. [19] compared CNN and SVM models for AF classification in ambulatory settings, finding that CNN achieved a superior 92.4% accuracy. Their study emphasizes the importance of deep learning's feature extraction capabilities over traditional machine learning models for capturing ECG nuances. X. Zhang et al. [20] developed a bi-channel neural network that utilizes frequency-time spectrum and Poincaré plot features from denoised single-lead ECG signals. This model achieved 95.2% accuracy, proving effective in noisy environments, such as wearable devices, by enhancing signal clarity and feature extraction. Z. Yu et al. [21] employed a dual-channel CNN with data augmentation to detect AF in short-term single-lead ECGs, attaining a high accuracy of 97%. This technique focuses on enhancing feature generalizability from brief ECG segments, beneficial for rapid screening applications.

J. Kim et al. [22] integrated a 1D U-Net with an RNN for AF prediction in noisy ECG conditions. The framework, which achieved a 94% prediction accuracy, was designed to capture temporal patterns critical to identifying early AF onset despite signal interference. P. Zhang et al. [23] explored a semi-supervised learning model for AF detection in Holter-monitor data, reducing the need for annotated ECG data by utilizing a combination of labelled and unlabelled data. This approach yielded a 92.7% accuracy and offers a cost-effective solution for data-limited scenarios in clinical settings. X. Li et al. [24] introduced a time-adaptive densely connected neural network to address the challenges of data imbalance and feature enhancement in variable-length ECG recordings. This model achieved 96.5% accuracy by optimizing temporal data handling and adjusting for data scarcity. M. R. Suri et al. [25] implemented a Bayesian-optimized CNN ensemble for AF detection in single-lead ECG data, reaching an accuracy of 94.8%. By incorporating Bayesian optimization, the model demonstrates increased robustness in identifying complex arrhythmic patterns.

L. Wang et al. [26] combined GAN-based data augmentation with Poincaré recurrence plots to balance ECG datasets for AF detection, achieving a 93% accuracy. This approach addresses data scarcity by generating synthetic AF samples, enhancing model training on imbalanced datasets. S. Chen et al. [27] presented a bi-directional LSTM network using heart rate variability (HRV) features extracted from ECGs, which improved early AF detection accuracy to 95.3%. By focusing on HRV, this model aims to identify AF onset in initial stages, supporting preventive health measures. J. Lee et al. [28] proposed a dual-channel CNN architecture for ECG signal segmentation and AF detection, achieving a 96% accuracy. This design enhances heartbeat segmentation and feature extraction, proving effective for single-lead ECG analysis in ambulatory settings.

H. Zhao et al. [29] introduced a fiducial-free 1D CNN for detecting AF in wearable ECG devices, obtaining a 94.6% accuracy. This model bypasses the need for specific fiducial points, making it suitable for continuous monitoring on consumer-grade wearable devices. F. Zhou et al. [30] developed a semi-supervised deep learning model to detect AF in wearable ECG data with minimal labeled samples, achieving a 91.8% accuracy. This method offers a scalable solution for deploying AF detection algorithms in resource-limited or data-sparse

settings. A. Rahman et al. [31] designed a dynamic ensemble model combining CNN and LSTM architectures to provide real-time AF detection, achieving an accuracy of 95.9%. This hybrid approach addresses the need for continuous monitoring and adaptive detection in mobile health applications. T. Yin et al. [32] incorporated an attention mechanism within a CNN framework to improve AF classification in ambulatory ECG data, reaching a 94.2% accuracy. The attention mechanism enhances the model's ability to weigh crucial ECG features, providing robust AF detection for wearable devices.

G. Xu et al. [33] developed a hybrid CNN-RNN model for multi-class AF detection using 12-lead ECG recordings, achieving a 96.3% accuracy. This approach allows the detection of various AF types, enhancing the model's clinical applicability for complex arrhythmic classification. R. Cheng et al. [34] combined GAN-based data augmentation with an LSTM ensemble to manage data imbalance in ECG datasets, achieving a 93.5% accuracy. This model proves effective in maintaining high performance on imbalanced data, such as sporadic AF episodes. S. Kim et al. [35] implemented a Transformer-based model to predict AF onset using ECG data, achieving a 96.8% accuracy. The Transformer network captures long-term dependencies within ECG data, making it particularly effective in early-stage AF prediction.

MATERials and Methods

In this section, we will describe the dataset used, preprocessing steps. Figure 2 visualizes the proposed approach.

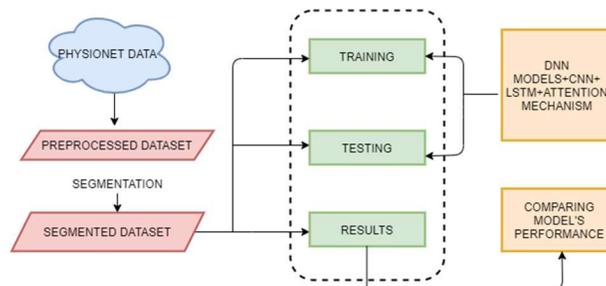


Figure 2: System Flow Chart

Dataset

For this study, we utilized the PhysioNet 2021 Paroxysmal Atrial Fibrillation (PAF) Detection Challenge Dataset as the primary data source, referenced in [36][37]. This dataset is part of the PhysioNet/Computing in Cardiology Challenge series, known for offering high-quality, standardized datasets focused on complex physiological data challenges. The PhysioNet 2021 dataset is specifically designed for AF detection, providing a rich array of ECG recordings ideal for training and evaluating deep learning models in the context of AF classification.

Data Composition:

The challenge data includes ECG recordings from leads I and II, offering long-term dynamic ECG signals that capture the variability associated with arrhythmias like paroxysmal AF (PAF). Each record is variable in length, sampled at a frequency of 200 Hz, which provides a high-resolution view of the cardiac cycles, essential for accurately detecting AF episodes.

Annotation Standards:

To ensure consistency and accuracy, the dataset annotations are structured in the WFDB (Waveform Database) format, following Physio Bank annotation standards. Each AF episode, for instance, is defined to include at least 5 consecutive heartbeats to avoid ambiguity in rhythm classification, thus ensuring high-quality, clinically relevant labeling. This structure is particularly advantageous for model training, as it offers well-defined and standardized annotations across all records.

Training Set:

The training set for this study consists of 730 individual recordings, covering a wide array of heart rhythm patterns, including both normal sinus rhythm and AF episodes. This substantial data variety within the training set enables models to capture nuanced patterns of AF, making it suitable for developing robust, generalizable deep learning algorithms.

Preprocessing Techniques Applied to ECG Signals

Preprocessing plays a critical role in enhancing the quality and interpretability of ECG signals for deep learning models[38]. In this study, we employed a two-stage preprocessing procedure to prepare the ECG signals: Normalization and Band-pass Filtration. Each step serves a unique purpose in improving the signal quality by reducing noise and aligning the data for optimal model performance.

Normalization:

Normalization is the first step in our preprocessing pipeline. This technique adjusts the amplitude range of ECG signals to a uniform scale, ensuring that each input signal has comparable data ranges. By standardizing the values across different recordings, normalization reduces biases that might otherwise impact the learning process, especially during gradient-based optimization in deep learning.

Process: Each ECG signal is transformed to have zero mean and unit variance, using the formula:

$$X_{\text{normalized}} = \frac{X - \mu}{\sigma}$$

where X represents the raw ECG signal values, μ is the mean, and σ is the standard deviation. This normalization process enhances the model's convergence speed by providing a more balanced input space, thus avoiding large deviations that could potentially disrupt the learning process.

Impact on Model Training: Normalization makes the model less sensitive to variations in signal amplitude due to individual differences among patients or equipment, leading to a more robust model capable of detecting AF across different scenarios.

Band-Pass Filtration:

Following normalization, each ECG signal undergoes band-pass filtration. This step is essential for removing noise and artifacts outside the frequency range relevant to AF detection. In ECG analysis, band-pass filtering is commonly applied to preserve the frequency components associated with heartbeats (typically between 0.5 Hz to 40 Hz) while eliminating higher-frequency noise (e.g., muscle noise or power line interference) and low-frequency drift.

Frequency Range: The filter is set to pass frequencies within 0.5 to 40 Hz, which captures essential cardiac rhythms without interference from extraneous frequencies.

Implementation: We applied a digital band-pass filter to attenuate frequencies outside the specified range. For example, we implemented a Butterworth filter, chosen for its smooth passband and effective attenuation outside the desired frequency band, providing a clean and interpretable signal.

Benefits: By restricting the frequency range to 0.5 to 40 Hz, we retain critical information needed for AF detection while filtering out irrelevant signals. This reduces noise and increases the signal-to-noise ratio, enabling deep learning models to focus on meaningful patterns related to heart rhythms.

Band-Pass Filtration

Following normalization, band-pass filtration was applied to each raw ECG signal to eliminate frequencies outside the desired range, which could introduce noise or irrelevant information to the data. Band-pass filters are particularly useful in ECG analysis as they preserve the frequency components associated with key cardiac events, like the QRS complex and P and T waves, which are essential for identifying atrial fibrillation (AF) and other arrhythmias.

Purpose of Band-Pass Filtering:

ECG signals contain multiple frequency components. For AF detection, the relevant frequencies lie within a specific range, typically between 0.5 and 40 Hz. Higher frequencies, such as those caused by muscle noise or power line interference, and lower frequencies from baseline drift, can distort the ECG signal, reducing model accuracy. Band-pass filtration isolates the signal components essential for detecting AF and removes these irrelevant frequencies, improving the signal quality and interpretability.

Filtering Range:

We used a 0.5 to 40 Hz band-pass filter:

Lower Bound (0.5 Hz): Eliminates baseline wander and low-frequency drift, which may arise from patient movement or sensor positioning.

Upper Bound (40 Hz): Removes high-frequency noise, such as power line interference and muscle artifacts, which can obscure key cardiac cycles.

Implementation:

A digital band-pass filter was chosen for its precision in eliminating unwanted frequencies while retaining critical features. Commonly, a Butterworth filter is applied due to its flat passband, which avoids frequency peaks or distortions that could otherwise alter the ECG signal. This setup ensures a smoother and clearer signal, optimal for machine learning models sensitive to noise.

Impact on Model Training:

Band-pass filtration ensures the model is trained on the essential cardiac signal elements without being affected by extraneous noise. By focusing on the ECG components relevant to AF, the model can learn distinctive features associated with arrhythmias, ultimately improving classification accuracy and model robustness in varied real-world settings.

Segmentation

Once the signals are normalized and filtered, they are divided into manageable 1-second segments, each labeled as AF (1) or non-AF (0). This segmentation process is crucial in training machine learning models for several reasons:

Focused Learning:

Segmenting ECG signals into 1-second intervals helps the model focus on smaller, more consistent patterns, reducing the variability introduced by longer ECG sequences. By working with shorter data intervals, the model can learn specific features related to the onset of AF without interference from unrelated rhythm patterns that may occur across a longer window.

High Temporal Resolution:

Using 1-second segments provides the model with high temporal resolution, allowing it to analyze changes in cardiac rhythms at a granular level. This segmentation enhances the model's ability to detect subtle variations in the ECG pattern, such as irregularities in R-R intervals or absent P waves—both hallmark features of AF.

Data Balance and Efficiency:

Segmenting the signals at regular intervals also ensures a balanced representation of AF and non-AF data points. This uniform segmentation allows for efficient training on a balanced dataset, preventing the model from overfitting to one category and promoting generalization. Additionally, the consistent segment length simplifies the data structure, which speeds up training and reduces computational overhead.

Accurate Labelling:

By dividing ECG signals into 1-second segments and labelling each, the training data becomes more precise. Each labelled segment represents a distinct state (AF or non-AF), enabling the model to recognize even short

episodes of AF. This structure improves the model’s detection accuracy and makes it suitable for real-time applications, where timely identification of AF is critical.

Training and Testing Set Division

The final step in the data preparation pipeline is splitting the pre-processed segments into training and testing sets. We used an 80:20 split, with 80% of the data allocated for training and 20% reserved for testing. This division is essential for assessing the model’s generalizability and performance on unseen data.

Training Set (80%):

The training set consists of 80% of the segmented and labeled ECG data. This data is used to train the model, allowing it to learn and identify AF-related features. By exposing the model to a broad range of labeled ECG patterns during training, it can recognize the nuanced characteristics of AF episodes.

Testing Set (20%):

The remaining 20% of the data forms the testing set, used exclusively to evaluate the model’s performance on unseen data. By holding this data back from the training process, we ensure that the model’s ability to detect AF episodes is evaluated objectively, simulating real-world performance.

Significance of the 80:20 Split:

The 80:20 split is widely accepted in machine learning because it provides a sufficient amount of data for training while reserving enough data to conduct a meaningful evaluation. This balance ensures the model can learn effectively while also providing a reliable indication of its performance in practical applications. Testing on this unseen data gives a realistic estimate of how well the model will perform on new ECG recordings, which is critical for clinical deployment.

Algorithm 1: LSTM Training

```

Input: Dataset D, Individual ECG sample S, LSTM layers L, Current Timestamp t, Input Sequence Length T.
Output: Classified Signal
1 for each S in D do
2   for each Li in L do
3     for each t in T do
4       Project Si over H;
5       Output of Current timestamp is fed
        Along with input in next timestamp
        t+1;
6     end
7     Output from last timestamp is input for
        next LSTM layer Li+1;
8   end
9   Output from Last Layer Ln is fed to FC layer;
10  FC layer Classifies the Signal S as AF or Not AF
    (0/1);
11 end
    
```

Algorithm 2: CNN Training Algorithm

```

Input: Dataset D, Individual ECG sample S, LSTM layers L, Current Timestamp t, Input Sequence Length T
Output: Signal
1 for each S in D do
2   for each Li in L do
    
```

```

3                                     for each Stride in Strides do
4         Perform convolution operation with
           Kernel/Filters.
5     end
6     Output sequence is fed to the next layer
           Li+1.
7                                     end
8     Flattened Output Sequence from Last Conv
           Layer Ln is fed to the FC Layer;
9     FC layer Classifies the Signal S as AF or Not AF
           (0/1);
10                                    end
    
```

Deep Learning Models

LSTM: LSTM networks are pivotal in the detection of AF within ECG signals due to their specialized architecture for handling sequential data [39]. AF detection relies heavily on capturing irregularities in heart rhythm patterns, which LSTM networks excel at by effectively modelling long-term dependencies in ECG time series data. It possesses a memory cell capable of storing information for long durations, enabling them to retain context and learn from dependencies in data that span extensive timeframes, allowing them to learn complex temporal dynamics inherent in AF, such as irregular heartbeats and variations in heart rate. By processing ECG signals sequentially, LSTMs can discern subtle patterns and abnormalities that indicate AF, even amidst noise and variability commonly found in clinical ECG recordings. The steps for training LSTM is detailed in Algorithm 1. The CNN training algorithm is demonstrated in Algorithm 2.

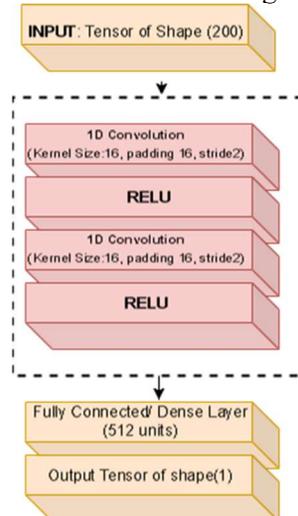


Figure 3: CNN Based Classifier

In Figure 3 Two 1-dimensional convolution layers were present in the first deep learning model. These layers made use of filters (Kernels) that produced feature maps based on the input features. We modified the padding and stride for each convolutional layer. The output is then passed through a fully connected dense layer consisting of 512 neurons, which processes the information and generates a scalar output that represents a binary classification (AF or Normal). The CNN automatically learns various features from the signals and categorises them using those features. Convolution, pooling, and fully connected layers make up a standard CNN model. Both 1-D convolutional layers utilized the ReLU activation function.

Bi-LSTM

Bi-LSTM sequences information in two directions one from the start to the end (forward LSTM) and another

from the end to the start (backward LSTM). This bidirectional processing allows Bi-LSTMs to capture not only temporal dependencies but also contextual cues from both preceding and succeeding time steps[40]. In the context of AF detection, Bi-LSTMs can effectively capture the irregularities and patterns indicative of AF across the entire ECG signal. By integrating information from both directions, Bi-LSTMs enhance the model's ability to discern nuanced features and subtle variations in heart rhythm that are critical for accurate diagnosis.

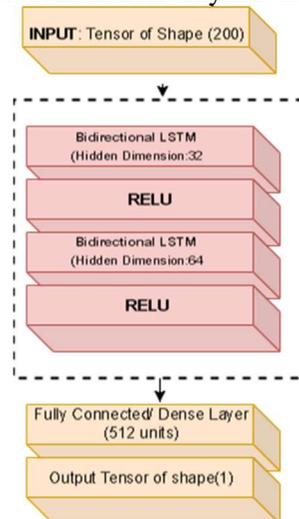


Figure 4: LSTM Classifier

The second architecture in Figure 4 employed two LSTM layers that succeeded one another. The gradient vanishing problem was addressed, and term dependencies from the input were increased using LSTM. Each LSTM layer comprised three essential gates: the input gate, forget gate, and output gate. The input gate updates the memory cell based on new inputs, while the output gate generates predictions through an activation function. In contrast, the forget gate resets the memory cell to zero, allowing the model to discard irrelevant information. To reduce overfitting, dropout regularisation was added after each LSTM layer. In both LSTM layers, ReLU was the activation function used.

Attention Mechanism

The attention mechanism enhances the detection of AF in ECG signals by dynamically focusing on the most relevant parts of the input sequence. In AF detection, ECG signals can vary significantly in duration and complexity, making it challenging to identify crucial segments indicative of irregular heart rhythms. The attention mechanism addresses this challenge by assigning weights to each time step of the input sequence based on its importance in relation to the task at hand.[41] This allows the Bi-LSTM network to prioritize segments that exhibit characteristics of AF, such as irregular heartbeats or specific waveform patterns like fibrillation waves. By incorporating attention, the model can effectively learn to emphasize informative features while suppressing noise and irrelevant variations in the ECG signal.

Attention based CNN- BiLSTM Model

The architecture in Figure 5 follows a similar flow to the previous model, with the CNN and LSTM layers operating in tandem. However, their outputs are now separately processed by distinct Self-Attention Layers, which selectively focus on crucial elements and suppress irrelevant information. The refined outputs are concatenated and are fed into a FC layer consisting of 1024 units, ultimately producing a binary scalar output (0-AF or 1-Normal).

We developed a method leveraging a bidirectional LSTM network with attention mechanism, designed to selectively focus on the most influential signal components and filter out noise. By identifying the signals with By identifying the signals that most significantly influence the final output (AF or non-AF classification), the attention-based network enhances the model's accuracy. Prior to input, the signals undergo pre-processing to optimize the data for analysis. The LSTM layer projects every time-step in

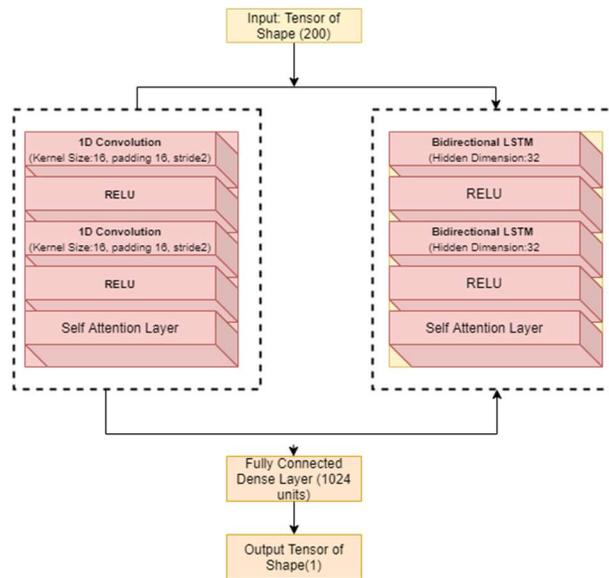


Figure 5: Attention based CNN+LSTM Classifier

the sequence into a vector of the hidden dimension size. This vector is fed directly into the embedding layer. This layer provides embedding weights for every segment and it's replaced with it. Now this input is fed into the LSTM layer which is bi-directional. At every time step, we take the current input and the previous input and then feed it into the LSTM layer. Thus, all of these hidden states are combined and moved to two dense layers which are fully connected. A single neuron, as usual, performs the final categorization

Results

All experiments are implemented using Python 3.9, PyTorch, Numpy library etc. All experiments were conducted on Intel i5 processor 4GB RAM. The proposed model's accuracy, sensitivity, and specificity are among the performance measures that are used to evaluate its performance. Table 1 shows the classification accuracy of proposed model with existing ones and Table 2 illustrates the classification of AF. The values in the Table 2 suggest that the model is effective at distinguishing between AF and normal.

Table 1: Training and Validation Accuracy of Distinct Models

Architecture	Training	Validation
Simple CNN	98.3	96
CNN	98.6	96.2
Enhanced with LSTM		
ATTN-CNN-Bi-LSTM	98.6	98.2

Table 2: Category-Wise Performance

Category	Acc	Sensitivity	Specificity
AF	98	97	98
Normal	99	99	99

Validation Performance: The model's performance on validation data is crucial for assessing its real-world applicability. The integration of LSTM layers and the attention mechanism into the CNN architecture enhances

the model's performance on this validation set, indicating its robustness and reliability in practical scenarios .
 Comparison with Existing Models: The proposed model's performance is compared with existing architectures, showing that it outperforms them in terms of classification accuracy. This comparative analysis further validates the effectiveness of the model in detecting AF .

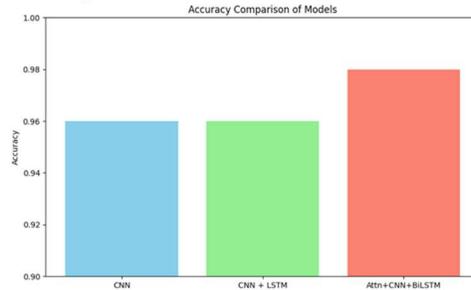


Figure 6: Accuracy Comparisons of Models

Figure 6 shows the accuracy comparison across the three models: CNN, CNN + LSTM, and CNN + Attention + Bi-LSTM. We observe that CNN + Attention + Bi-LSTM model attained a higher accuracy of 98%. This improvement indicates the effectiveness of incorporating attention mechanisms and bidirectional LSTM layers in enhancing model performance.

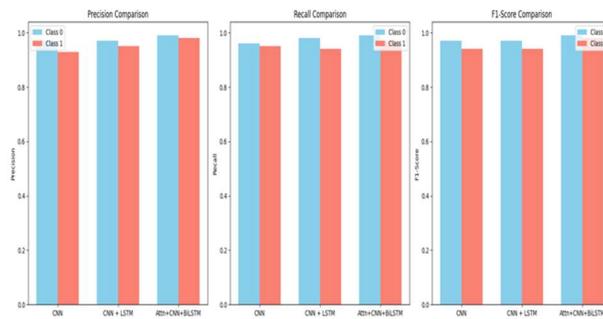


Figure 7: Performance metrics for each class

Figure 7 depicts the precision, recall, and F1-score for each class (Class 0: non-AF, Class 1: AF) across all three models. Each subplot represents one metric:

In the Precision Comparison subplot, the CNN + Attention + BiLSTM model demonstrates the highest precision, with values of 0.99 for Class 0 and 0.98 for Class 1. This highlights the model's ability to minimize false positives for both classes.

In the Recall Comparison subplot, the CNN + Attention + BiLSTM model again shows the highest recall scores, particularly in Class 0, with a value of 0.99. This reflects its proficiency in accurately identifying true positives.

The F1-Score Comparison subplot shows that CNN + Attention + BiLSTM achieves the highest F1-scores, indicating a balanced performance between precision and recall for both classes.

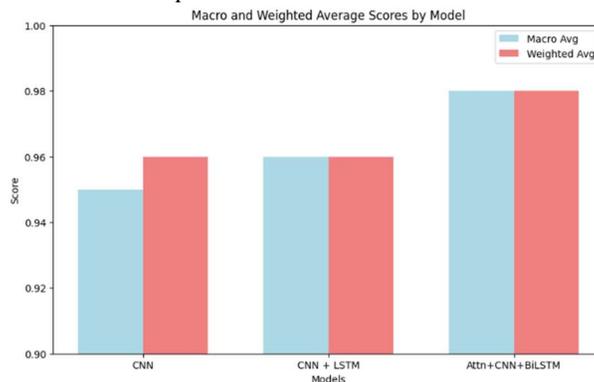


Figure 8: Macro and Weighted Average

performance comparison

Figure 8 illustrates the macro and weighted averages for precision, recall, and F1-score across all three models. The CNN + Attention + BiLSTM model shows the highest scores for both the macro and weighted averages, with values of 0.98. This finding underscores the model's robustness in handling the imbalanced dataset, performing consistently well for both classes, and achieving the best overall performance among the tested models.

Discussion

The study achieved a remarkable classification accuracy of 98% for detecting atrial fibrillation (AF) using the CNN-bidirectional LSTM with Attention model. This highlights the potential of deep learning techniques in enhancing the accuracy of ECG signal analysis, which is crucial for timely diagnosis and treatment of AF. Unlike previous research that heavily relied on manual feature engineering, this study utilized deep learning algorithms to automatically extract features from ECG signals. This shift not only streamlines the detection process but also improves the model's ability to identify complex patterns associated with AF.

The architecture of the models used, such as the CNN and LSTM components, suggests that they can capture both spatial and temporal features from the ECG data. The CNN is effective in recognizing spatial hierarchies in the data, while the LSTM component is designed to handle sequences, making it suitable for time-series data like ECG signals. The incorporation of an Attention mechanism in the CNN-bidirectional LSTM model allows the model to focus on specific parts of the ECG signal that are more relevant for detecting AF. This enhances the model's ability to discern important features from the noise present in the ECG data, leading to improved classification accuracy. The automatic extraction of features through these advanced deep learning techniques not only simplifies the detection process but also enhances the model's performance, achieving a high classification accuracy of 98% for AF detection. This demonstrates the potential of using automated methods in clinical settings for timely and accurate diagnosis.

The findings have significant clinical implications, as early detection of AF can prevent serious health issues, including strokes. The proposed model could serve as a valuable tool for healthcare professionals, enabling them to make informed decisions quickly and improve patient outcomes. It is important to acknowledge the limitations of the study, such as the reliance on the "China Physiological Signal Challenge 2021" database, which may restrict the generalizability of the results. Future studies should consider validating the model on diverse datasets to ensure its robustness across different populations.

Future research could explore the integration of additional features or real-time monitoring capabilities to enhance the model's applicability in clinical settings. Testing the model on larger and more varied datasets will also be essential to confirm its effectiveness and reliability in diverse clinical scenarios. In conclusion, the study underscores the importance of leveraging advanced deep learning techniques for AF detection. The promising results pave the way for further research aimed at improving diagnostic tools and ultimately enhancing patient care in the field of cardiology.

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