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Detection of Atrial Fibrillation using a Feedforward Sequential Model

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Abstract. Atrial Fibrillation (AFib) and its associated symptoms are significant problems that doctors and several studies have attempted to solve throughout the years. It is diagnosed by analyzing a patient's electrocardiogram (ECG) data. However, continuous efforts have been made to develop an algorithm that detects AFib with optimal efficiency and cost-effectiveness. In this study, a sequential model was used based on feedforward neural network as this is arguably the simplest algorithm developed and requires minimal computing power. The results showed that training the algorithm for 1000 epochs yielded the best results. Further studies showed that using a combination of 10-fold cross-validation and blindfold validation proved an ideal way to determine the model's capabilities in distinguishing patients with AFib from those without. In conclusion, the developed model successfully distinguished between AFib and non-AFib patients with a 96.67% sensitivity, 94.61% specificity, and 95.64% accuracy.

Keywords: Atrial fibrillation; ECG; Feedforward neural network; Sequential method

1. Introduction

Arrhythmia is an irregularity in the heartbeat, manifesting as an increase or decrease in the heart's speed (MedlinePlus, 2016). The most common type of arrhythmia is atrial fibrillation (AFib). Patients with AFib frequently overlook symptoms, unaware that they are manifesting signs of potential heart problems. This leads to an estimated half of AFib patients being undiagnosed (Atrial Fibrillation Association, 2012). In 2010, it had an estimated global age-standardized prevalence of 0.5%, with this expected to double by 2030 (Patel *et al.*, 2018). Afib has also been associated with an increased risk of numerous cardiovascular conditions, such as heart failure, stroke, and sudden cardiac death (SCD) (National Health Services, 2021; Ahmed and Zhu, 2020; Rattanawong *et al.*, 2018; Odutayo *et al.*, 2016; Pistoia *et al.*, 2016). Therefore, early detection of AFib is necessary as it would lead to effective management and improved patient outcomes (Hill *et al.*, 2019).

EACTS' 2020 ESC Guidelines for the diagnosis and management of AFib (Hindricks *et al.*, 2020) state that the standard device used for detection is the 12-lead ECG. However, for patients above 65 years, a cost-effective alternative is pulse palpation. Taggar *et al.* (2015)

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reported a high false positive rate using pulse palpation, with a sensitivity and specificity of 0.92 and 0.82, respectively, a positive likelihood ratio (PLR) of 5.2, and a negative likelihood ratio (NLR) of 0.1. This suggests a need to develop an algorithm that can accurately detect the presence of AFib while maintaining its cost-effectiveness.

Several studies have explored machine learning, with most model using Recurrent Neural Network (RNN) and R-R intervals to detect AFib. However, RNN is a complex algorithm and contrasts with Feedforward neural network, which is the most straightforward algorithm devised (Poznyak, Oria, and Poznyak, 2019). In this model, information is passed only in a single direction, moving from the input nodes through the hidden nodes until it reaches the output nodes. The simplicity of network makes it more manageable to operate and reduces the need for robust and expensive devices for processing the data.

1.1. Atrial Fibrillation

One of the most common cardiac arrhythmias being treated is AFib. Arrhythmia refers to a change in the speed of the heartbeat. When a person has AFib, the atria experience irregular beating, causing poor blood circulation from the atria to the ventricles. It may occur in isolated incidents or be a chronic illness (Cai *et al.*, 2020). The prevalence of AFib is increasing, with a 25% lifetime risk over the age of 40. Furthermore, complications include hemodynamic instability, cardiomyopathy, heart failure, and embolic events such as stroke.

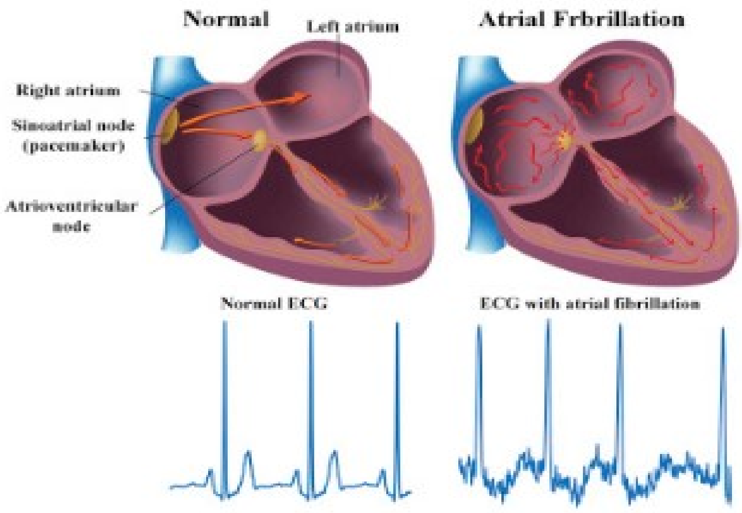


Figure 1 Illustration of the P Wave, QRS complex, and T wave signal of the ECG

Figure 1 shows an ECG waveform with AFib and a waveform with a normal ECG, both taken from the dataset used in this study. The P wave, QRS complex, and T wave constitute a normal waveform. In contrast, an AFib waveform shows several inconsistent fibrillatory waves (F waves) replacing the P wave, accompanied by R-R irregularities (irregular intervals between successive R waves on the ECG). AFib can be diagnosed through a patient's ECG data, with features including [a] irregularly irregular rhythm, [b] absence of P-wave, [c] variable ventricular rate, [d] QRS complexes usually less than 120ms, [e] fibrillatory waves that may be fine or coarse (amplitude of <0.5 mm or >0.5 mm respectively), and [f] fibrillatory waves mimicking P-waves, leading to misdiagnosis (Burns and Buttner, 2018). Deep neural network (DNN) have gained popularity for solving classification, segmentation, and detection issues. Several deep learning algorithms have been used for AFib detection, including the convolutional neural network (CNN), RNN, and autoencoder. With deep learning, R-peak detection and removal of noises alleviate the burden of manual labor.

1.2. AI Algorithms

Episodes of AFib are often paroxysmal, requiring manual diagnosis. Therefore, real-time cardiac monitoring with wearable health trackers is required for the early detection of arbitrary events (Panindre, Gandhi, and Kumar, 2020). By using instantaneous heart rates (IHR) beat-to-beat variations of AFib could be classified using the accuracy, sensitivity, specificity, precision, F1 score, recall, and area as criteria for evaluation and comparison.

Table 1 Comparison of performance of different supervised learning algorithms

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	AUC (%)	Specificity (%)	Training Duration (seconds)
Logistic Regression	61.92	51.14	3.16	5.95	55.03	98.14	811
AdaBoost	61.60	49.03	17.47	25.76	63.66	88.80	46,504
Gaussian Naïve Bayes	62.90	52.13	33.26	40.61	65.96	81.17	235
kNN	74.99	79.24	46.82	58.86	77.56	92.41	1,456,010
Decision Tree	73.54	65.26	65.48	65.37	71.99	78.51	52,896
Random Forest	81.89	79.15	71.30	75.02	90.35	88.42	3,129,625
SVM - Radial Basis Function Kernel	72.26	72.07	43.80	54.49	78.61	89.63	1,277,600
LSTM	67.20	56.49	61.11	58.68	75.39	70.95	9,663
Bi-LSTM	89.75	90.37	81.84	85.89	96.48	94.62	167,056

As shown in Table 1, several machine learning algorithms were trained and tested with a dataset in PhysioNet using an NVIDIA Tesla V100 GPU of 32 GB memory. According to the results, the Gaussian Naïve Bayes algorithm had the shortest training duration, but its results were not promising compared to other algorithms. On the contrary, the Bi-LSTM algorithm had the best performance among all the nine tested algorithms. Additionally, Faust *et al.* (2018) applied Bi-LSTM with R-R interval signals, achieving an accuracy of 98.51% and 99.77% after 10-fold cross-validation and blindfold validations.

A possible reason for the superior performance of RNNs over other network is their ability to overcome the critical impediments of using standard machine learning algorithms. This includes the presumption that inputs and outputs in model are independent of each other (Schmidhuber, 2015). RNNs achieve this by permitting network to retain or use state data, colloquially called "memory" which captures all input data.

Aside from RNNs, CNN are also used to detect AFib because they require no manual feature extraction (Murat *et al.*, 2021). Reinforcement learning (RL) methods have been applied to address challenges in traditional machine learning tasks, particularly those emphasizing classification and the prediction process or sequential processes such as budgeted classification and time prediction). In addition, the evolution of deep architectures, or DNN from Neural Network (NN), has expanded its applications, including but not limited to image classification, audio recognition, machine translation, and natural language processing. NN is a sequential decision process that chooses one mapping from a group of candidate mappings at each layer of a deep design. On the other hand, the Deep Sequential Neural Network (DSNN) model processes input through a series of local rather than global transformations.

Denoyer and Gallinari (2014) compared two alternative model, including (1) NN or primary neural network and (2) DSNN-k or sequential model, where k is the number of possible actions. The initial trials were conducted on five University of California Irvine (UCI) datasets, which are low-dimensional datasets with around 1,000 training samples. These results showed that using more complex architectural designs did not improve the performance of models for specific datasets (diabetes, heart). In these cases, a basic linear model was adequate for computing results with high accuracy. Therefore, the DSNN strategy performed better than the NN method, particularly when the number of children per node is small.

1.3. Metrics

Diagnostic accuracy measurements include sensitivity, specificity, predictive values, likelihood ratios, the area under the ROC curve, Youden's index, and diagnostic odds ratio (Pennsylvania State University, 2013). This study focused on sensitivity and specificity, which provide necessary measurements for patient screening. Sensitivity or True Positive Rate (TPR) provides a measurement of how effectively models could identify positive instances, while specificity or True Negative Rate (TNR) measures the proportion of true negatives. A model with high specificity shows that it could almost flawlessly identify the negative results. Ideally, models should be highly sensitive and specific, but trade-offs occur between these measurements as they are inversely proportional (Shreffler and Huecker, 2023). A highly sensitive model captures most instances of positive results, dismissing fewer cases of the disease. In screening applications, model should achieve a higher specificity as it reduces false positives and minimizes unnecessary diagnostic procedures for patients.

2. Methods

2.1. Model Setup

Figure 2 illustrates the proposed system architecture, consisting of the raw ECG data, an input layer with 512 nodes, three hidden layers of 256, 64, and 32 nodes, and a single output layer. Following the input layer, a 10% dropout was applied before passing through the first hidden layer to prevent overfitting. The size of the input layer was matched with the number of data points in a single window. This architecture is based on Feedforward neural network, where information passes through the layers once.

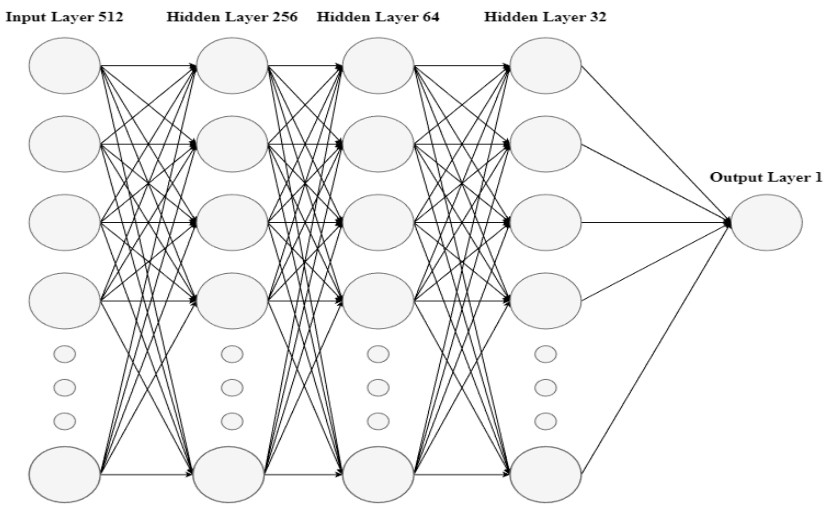


Figure 2 Proposed System Architecture

The dataset used was the MIT-BIH Afib Database (Goldberger *et al.*, 2000), comprising 10-hour ECG recordings at 250 samples per second from 23 patients at Beth Israel Deaconess Medical Center. It provided rhythm annotations (.atr) for AFib, AFL (Atrial Flutter), J (AV junctional rhythm), and N (Normal) to represent all other rhythms. Figure 3 shows a sample of a 1-minute recording with rhythm annotations, processed with Python using the WFDB toolbox. Additionally, manually corrected beat annotation file (.qrsc) was used to detect the location of R-peaks. said it was observed that through these files, the different annotations could be visualized in the recordings, with N and AFib annotations presented in red and green, respectively.

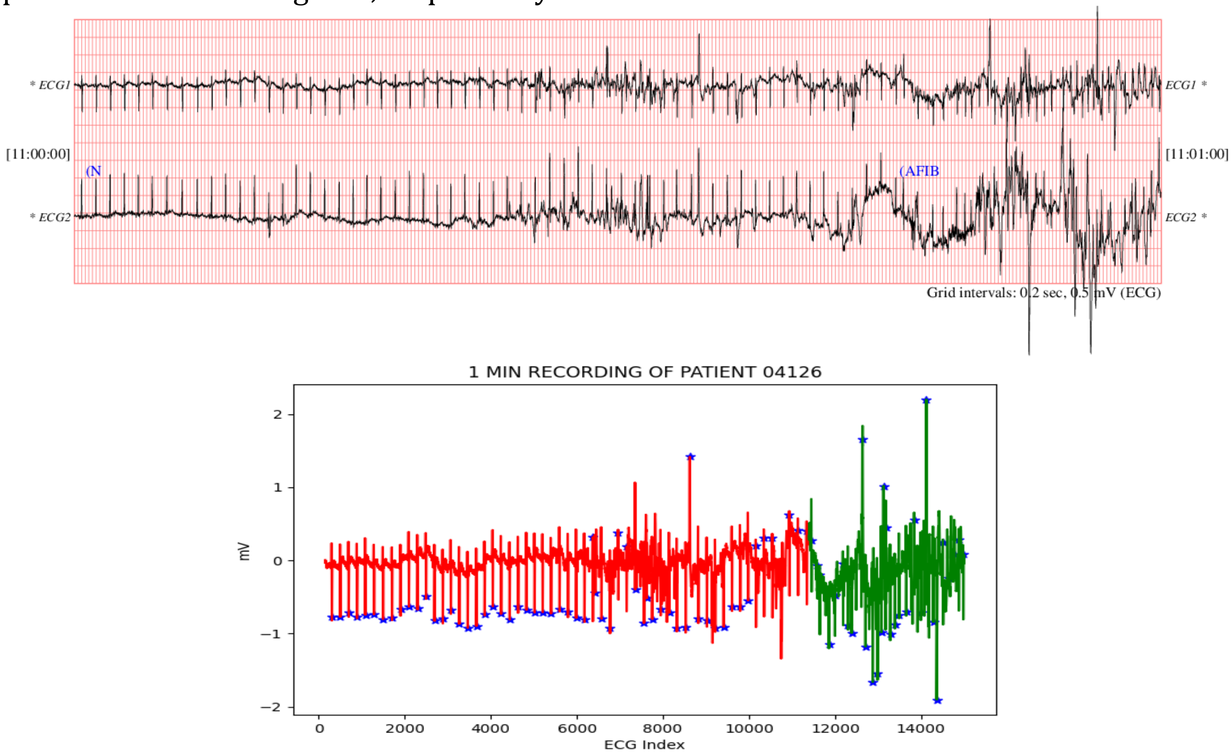
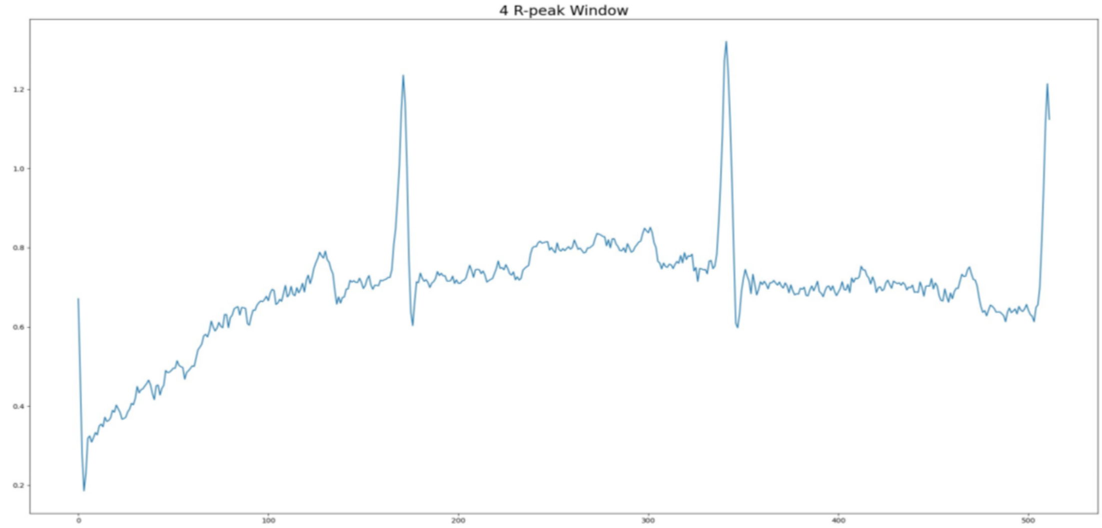


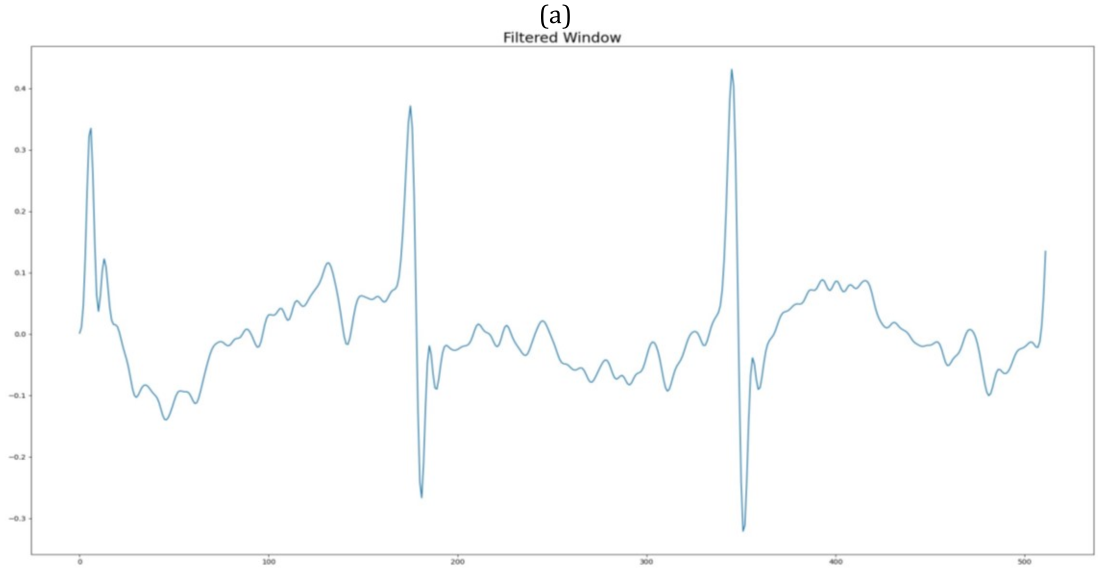
Figure 3 A sample recording of manual annotations and Python reading of raw data.

The location of a record's R-peaks was stored in an array. A random index (a random R-peak) was then chosen, along with the next three indices to create a window, as shown in Figure 4. Each window contained either N or AFib annotations, and windows with different annotations were disregarded. Furthermore, the average number of samples within a three-RR-cycle window was 544. This was resampled for uniformity to 512, which is the nearest integer to the power of 2.

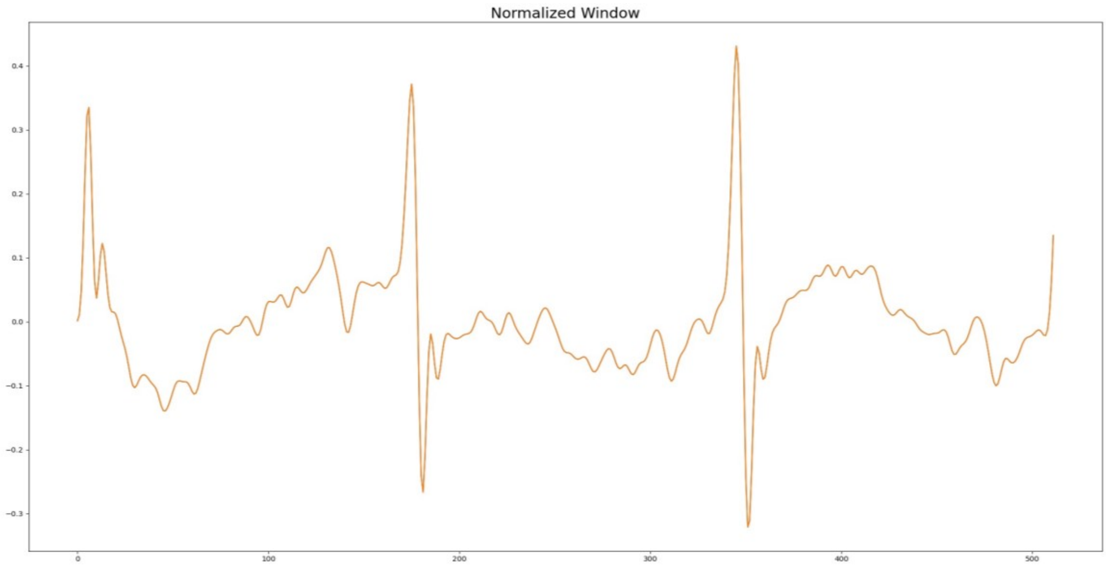
A single window consists of three RR cycles with a length of 512 data points. A Bandpass Filter with a low and high pass cutoff frequency of 35Hz and 1Hz, respectively, was applied to the signals. The amplitude of the signals was then scaled to return values between 0 and 1. The signals were then arranged row-wise, with each window written to a single row. AFib-annotated signals (Positive) were labelled as "1", while those annotated with N (Negative) were labelled as "0" before saving them separately into a CSV file. The program adopted a 25% test and 75% train split. Furthermore, multiple NumPy files (npz) were saved from the dataset for model fitting and evaluation. The program, modelled with low computing power applications in mind, was based on a Sequential Model with three layers, excluding the input layer. The network used an input layer of size 256, two hidden layers with sizes 64 and 32, and an output layer of size 1. Model was evaluated using 10-fold cross-validation and blindfold validation.



(a)



(b)



(c)

Figure 4 Illustration of the (a) Windowed, (b) Filtered, and (c) Normalized Raw Data

3. Results and Discussion

The proposed model was trained using an NVIDIA RTX 3060 GPU with 12GB memory. Each epoch took approximately 0.446 s to train, with the number of epochs set to 1000 based on previous training results showing a sudden drop in accuracy beyond this point.

3.1. Validation Results

The confusion matrix and the Receiver Operating Characteristic (ROC) Curve of the 10-fold cross-validation are shown in Figure 5. The ROC curve measures the model's ability to correctly distinguish classes. The closer the value is to 1, the better it can distinguish between classes. A summary of the results can be seen in Table 2. Based on the cross-validation results, the model returned a 0.9751 ROC curve, signifying that it accurately distinguished the two classes. Additionally, the model exhibited higher sensitivity than specificity, implying that it can better predict patients with a disease than without.

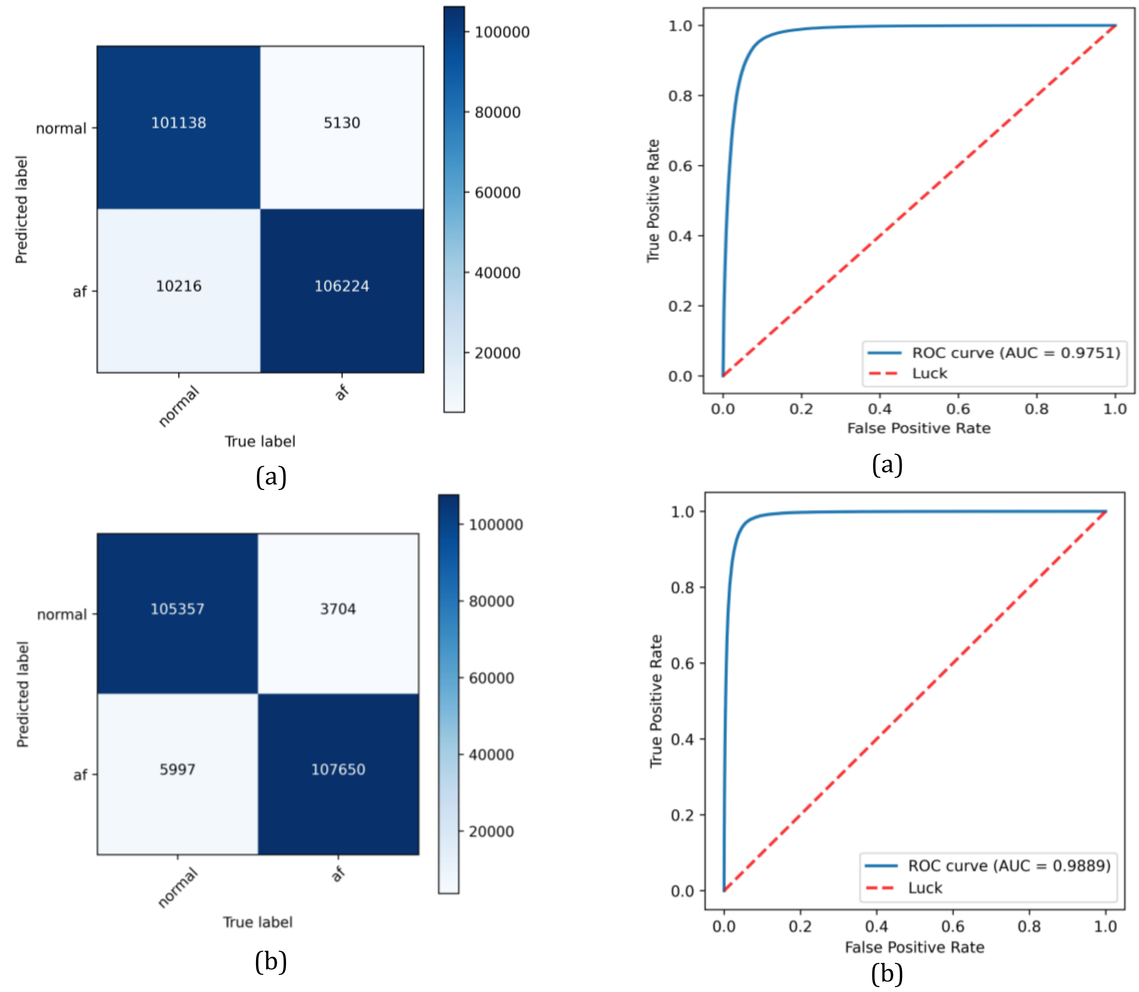


Figure 5 Confusion Matrix and ROC Curve of the (a) 10-fold and (b) blindfold validation

Table 2 Summary of 10-Fold Cross-Validation and Blindfold Validation Performance

Validation Type	TP	TN	FP	FN	Sensitivity	Specificity	Accuracy	AUC
10-Fold Cross-Validation	106,224	101,138	10,216	5,130	95.39%	90.83%	93.11%	97.51
Blindfold Validation	107,650	105,357	5,997	3,704	96.67%	94.61%	95.64%	98.89

3.2. Discussion

Data is one of the most prominent limiting factors in machine learning. Real-life applications of machine learning model require a larger dataset than was used in this study. The dataset was also balanced between AFib and non-AFib patients, which is not representative of the real-world population. Therefore, the model is expected to have a bias toward high sensitivity and false positives. Its performance can be compared to other studies that used the same dataset, most of which were also cited in (Faust *et al.*, 2018), but with additional studies added.

Table 3 Performance of another model using the same dataset

Author	Data pre-processing	Feature extraction method	Analysis method	Results
Zhou *et al.*, (2014)	Median filter	Shannon entropy	Threshold evaluated with ROC	Sensitivity of 96.72%, Specificity of 95.07%, Accuracy of 96.05%
Petrenas, Marozas, and Sörnmo (2015)	8-beat sliding window	Median filter and threshold for data labeling	Threshold	Sensitivity of 97.1%, Specificity of 98.3%
Henzel *et al.*, (2017)	Beat by beat evaluation, Windows of varying length to extract statistical features.	4 statistical features and the beat itself	Generalized Linear Model evaluated with ROC	Accuracy 93%, Sensitivity of 90%, Specificity of 95%
Faust *et al.*, (2018)	100 beat window, 99 beats overlap.	None	Recurrent neural network	Cross-validation and Blindfold validation Accuracy: 98.51%, 99.77% Sensitivity: 98.32%, 99.87% Specificity: 98.67%, 99.61% Positive Predictive Accuracy: 98.39%, 99.72%
Chen *et al.*, (2022)	Wavelet transform, sliding window	RR-interval	Feedforward Neural Network	Cross-validation: Accuracy of 84%, Sensitivity of 84.26%, Specificity of 93.24%.
Proposed Model	3 R-R cycle window, 1-35 Hz Bandpass Butterworth Filter, Normalized to 0-1.	Annotations provided in the dataset	Feedforward Sequential Model	Cross-validation and Blindfold validation Accuracy: 93.11%, 95.64%, Sensitivity: 95.39%, 96.67%, Specificity: 90.83%, 94.61%

Table 3 shows that the proposed model used a different method for predicting AFib aside from R-R intervals. Although this method achieved scores comparable with other studies using R-R intervals, most models still performed better. This could be attributed to the heavy focus on developing a simple model and an insufficient complexity in capturing the relationship between the input and output variables. A similar study by Chen *et al.* (2022) also used the Feedforward model and reported a cross-validation accuracy of 84%, a sensitivity of 84.26%, and a specificity of 93.24%. Comparing the proposed model to Chen *et al.* (2022), it performed better based on the metric scores. In terms of model complexity, the proposed model, with a total of 149,889 parameters, had a training duration of approximately 0.443s per epoch using the NVIDIA RTX 3060 GPU. Among the studies listed in Table 5, only Zhou *et al.* (2014) and Faust *et al.* (2018) provided data regarding complexity. Zhou *et al.* (2014) reported a training duration of 1.445s per 24 hours of data, yet it remained unclear whether this value corresponded to the training duration per epoch or the entirety of the training. The study also specified the use of an Intel Pentium(R) Dual-Core E5800 processor. Assuming the training duration was per epoch, it will be completed in only 0.443 seconds, making the proposed model faster. However, their model would be faster for a duration covering the entire training process. Faust *et al.* (2018) presented another model using a high-performance NVIDIA Quadro m5000 GPU tailored for industrial use with 343,301 parameters and a training duration of 215s per epoch (total of 80 epochs). In comparison, the proposed model had fewer parameters and a faster training duration, attributed to the unidirectional flow of information within the network. For replication purposes, the codes and datasets used in this study can be accessed through the link below: https://github.com/JanMichaelSantos/Detection-of-Atrial-Fibrillation-using-Feedforward-Sequential-Model.git

4. Conclusions

In conclusion, AFib is associated with an elevated risk of heart failure, stroke, SCD, and other heart-related diseases. Its global age-standardized prevalence is expected to double by 2030. This can be addressed through an early diagnostic system by analyzing a patient's ECG recording. Previous studies used various algorithms combined with R-R intervals for early detection. However, these necessitated hefty hardware. One objective of this study was to develop a cost-effective diagnostic system. Based on related literature, it was identified that sequential model could be implemented, using ECG features alongside R-R intervals to predict and accurately classify AFib and non-AFib patients. Model underwent training for 1000 epochs with a 75:25 train-test ratio and was filtered using a bandpass Butterworth with cutoff frequencies of 1-35 Hz. Upon evaluation, the 10-fold cross-validation and the blindfold validation performance yielded a 95.39-96.67% sensitivity, 90.83-94.61% specificity, 93.11-95.64% accuracy, and an AUC of 97.51-98.89%, respectively. Although other model developed showed higher performance on these metrics, they used complex algorithms that increased computation time. On the contrary, the proposed model had a simpler algorithm, making it more practical for implementations on small wearable devices with low computing power. It is recommended that future studies explore increasing the complexity of sequential model and use different datasets to gain a more comprehensive understanding of the model's performance on a broader representation. However, in implementing these recommendations, it is vital to consider the computing power of wearable devices.

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