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A model to enhance the atrial fibrillations' risk detection using deep learning

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ABSTRACT

Atrial fibrillation (AF) is a complex arrhythmia linked to a variety of common cardiovascular illnesses and conventional cardiovascular risk factors. Although awareness and improved detection of AF have improved over the last decade as the incidence and prevalence of AF has increased, current trends in using machine learning approaches to diagnose AF are still lacking in precision. To determine the true nature of the Electrocardiography (ECG) signal segments, a Convolutional Neural Network (CNN) model was employed to discover hidden information. Fully Connected (FC) layers were then utilized to categorize the ECG data segments as normal or abnormal. The suggested algorithm's findings were compared to state-of-the-art arrhythmia identification algorithms in the literature for the MIT-BIH ECG database. The methodology proved not only to yield high classification performance (98.5%) but also low processing computational advantage where the CNN was the most accurate algorithm used for atrial fibrillation detection hence. To conclude the findings of the research, a model was prepared to test the accuracy of the most common ML algorithms used for AF detection. After comparing the results of the experiment, it was clear that CNN algorithm is the best approach compared to Support Vector Machine (SVM) and K-Nearest Neighbor (KNN).

Keywords: Atrial fibrillation; Machine Learning; CNN.

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1. Introduction

Atrial fibrillation is a cardiac condition in which a random heartbeat (arrhythmia) causes blood clots, stroke, cardiac failure, and other consequences. Arrhythmia is a common heart rhythms disorder affecting 0.51% of worldwide population [1]. It's a disorder that affects the pace or rhythm of heartbeats, causing them to beat excessively rapidly, too slowly, or in an irregular manner. Irregular cardiac rhythm, or arrhythmia, can be a major concern. If left untreated, arrhythmias can cause serious problems, including heart arrest and stroke. The number of patients with this diagnosis is increasing rapidly over the recent years and AF is becoming a critical contributor to society mortality, as it increases in prevalence with aging of the population [2]. Fortunately, ECG test can often detect different heart diseases such as heart attack, an enlarged heart, or abnormal heart rhythms like Arrhythmia that may cause heart failure [1]. Bio-signals such as ECG are indispensable part of Tele-medicine systems nowadays for clinical medicine diagnosis, treatment, surgery, prognosis, and other purposes [1]. ECGs are now an essential part of the analysis and treatment of different cardiovascular diseases leading to effective heart health evaluation. Accurate detection of abnormal heart rhythms requires developing efficient algorithms for the support of clinicians to reduce the human effort as well as the error [2]. In this paper, the aim is to process a new model framework for arrhythmic beats detection which neglects the manual feature extraction, complex models (the number of features or the terms included in each predictive model), and long training time. The proposed model is utilized as a general classification technique for ECG data and accurate detection of different disorders. Numerous algorithms have been developed and a lot of work has already been done for classifying ECG data in the recent literature for arrhythmia detection [112]. Data pre-processing, feature extraction, and classification are three processes in the general classification method. The following is the outline of the paper: Section 2 will include the consist of literature review of past works in the topic. Section 3 will include the study methods for detecting aberrant cardiac rhythms, as well as the algorithms examined, the dataset and tools, experiment setup, and data processing. The results and analysis are discussed in Section 4. Section 5 wraps up the efforts of the reviewed findings on the task completed.

2. Background and literature review

Machine learning algorithms can detect AF with great precision while transmitting ECG data used in AF conformance. Vost et al. estimate that 3.8 million new AF diagnoses are recorded each year, with a global prevalence of 46.3 million [8]. It is important to note that, when the illness is asymptomatic or minimally symptomatic, it is difficult to diagnose. Initially, AF was diagnosed with a 12-lead electrocardiogram (ECG) or rhythm strip, as per European Union and US guidelines [9,10]. However, patients must undergo extra tests to diagnose their illnesses because these procedures entail pulse checking, which is not accurate in diagnostics. As a result, automated computerized methods that employ biomarkers to diagnose AF in patients are being developed to improve the accuracy of recognizing AF in patients.

Machine learning is a data analysis technique that includes automating analytical models in order for computers to learn from data and discover patterns of interest. Models that use machine learning approaches can provide better predictive values for estimating the incidence of AF [10]. The typical approach uses machine learning algorithms to exploit feature selection in deep learning approaches like supervised, semi-supervised, or unsupervised learning to detect AF automatically [19]. Deep neural networks (DNNs) and convolutional neural networks (CNNs) are two deep learning models that have been widely used to identify AF. [12, 15, 17, 20, 21, 24, and 25]. Using a hazardous data-driven model, machine learning may be utilized to determine the nonlinear relationship between variables [17]. This model can assist clinicians in making quick life-saving decisions by speeding up the diagnosing process. Machine learning may therefore be used to categorize and detect AF. lowering the death rate in humans with a prevalence of 2% AF [9]. Lim et al. established a method for identifying AF that uses feature selection to identify AF using ECG signal characteristics and heart rate discrepancy [17]. The effectiveness of this strategy is assessed using machine learning classifiers. On a different level, Lahdenoja et al. devised a method for detecting AF using data collected via a smartphone [18]. This system can extract features, preprocessing data to categorize it, making it extremely accurate in detecting AF. In this assessment, the CNN model showed to be the most effective in terms of maximizing the accuracy of the automated indicated using machine learning.

Table 1 lists the most common machine learning methods used in the field of AF [112]. In summary, several publications were analyzed to find the most prevalent algorithms and to showcase the results of each way of implementation. Depending on the amount of noise in the data set and other elements connected to the ECG signal that cause a disruption in the implementation process, various typical algorithms produce varying outcomes. As indicated in the table below, CNN algorithm had the highest accuracy of 96%, followed by the SVM and ML algorithms, both of which had a 95 % accuracy. The detection trees and STD method, on the other hand, had the lowest accuracy.

Table 1. Literature review on the most common atrial filtration classification algorithms accuracy.

No.	Citation	Algorithms (Classifiers)	Accuracy [%]
1	[97]	DL	95.7
2	[49]	KNN	96.2
3	[80]	ML Algorithms	96.5
4	[21]	SVM	97.4
5	[47]	SVM	97.4
6	[84]	SVM	96.79
7	[91]	SVM	96.64
8	[104]	KNN	96.08
9	[61]	CNN	96
10	[54]	CNN	95.9
11	[99]	ECG	95.5
12	[39]	CNN	97
13	[63]	Time-frequency pattern analysis	95
14	[110]	SVM	95
15	[111]	CNN	97
16	[41]	SVM	94.5
17	[59]	CNN	96
18	[73]	Deep CNN	94
19	[103]	Deep learning	93.6
20	[60]	ECG	92.6
21	[88]	CNN	96
22	[107]	KNN	91
23	[20]	CNN	97
24	[89]	SVM	90
25	[40]	CNN	97
26	[48]	LSTM	85.7
27	[100]	KNN	81.6

3. Methodology

The investigation covers a detailed analysis of studying the ECG signals using deep neural network models to recognize abnormal heart rhythms. Traditional approaches proposed for ECG data classification usually calculate statistical features and use them as learning parameters for machine learning models for classification task. Handcrafted selection of these features along with feature ranking normally are applied for better learning of the classifier model. For instance, priori-selected feature incurs information loss and undermines the efficiency of the system [1]. The handcrafted selection of ECG features is not feasible due to biasness of information. On the other hand, adaptive selection mechanism may improve the system efficiency as in sampling frequency [3], however, it will increase the computational cost which is not a practical approach. Same is the case for handcrafted feature selection methods [3]. For these reasons mentioned, the methodology of the proposed model will first calculate features and then chooses the most suitable that will contribute to increase computations as presented in Figure 1. Therefore, the proposed strategy is using a simple method by applying feature selection to allow for every individual ECG sample to be processed directly. Filters recognize linear patterns in the data, such as edges, by observing the changes in the image's intensity values. Consequently, the method requires two feature selection methods; instantaneous frequency and spectral entropy that are essentially concatenated to generate higher accuracy. The goal in this regard is to develop such a system with high classification performance and low computational complexity. The proposed arrhythmia detection methodology combines ECG signal segmentation and segment level classification of these signals using CNN. Figure 1 depicts a general overview of the proposed ECG signals classification scheme. The process starts with segmentation of ECG data and is followed by several trials consisting of 3 second data segment to gain the highest accuracy. As the database utilized in this study has 360 Hz sampling rate with two ECG electrodes, therefore, a single trial comprises of 360 × 3 × 2 array. Figure 1 depicts one ECG segment/trial used in this study. Signals corresponding to both normal and abnormal heart beats are presented while irrelevant observations are removed. This includes removing variables from your dataset that are duplicated, redundant, or unrelated. This specific segment of ECG signal is used as input to the CNN model. As we obtain the single dimensional data segments, the next phase in the process is to extract meaningful data from the database in order to investigate the signal's true nature, i.e., normal or abnormal heart rate. Proposed classification method uses deep neural networks to discriminate the nature of the ECG signal. A brief discussion over the CNN model is presented in section 3.

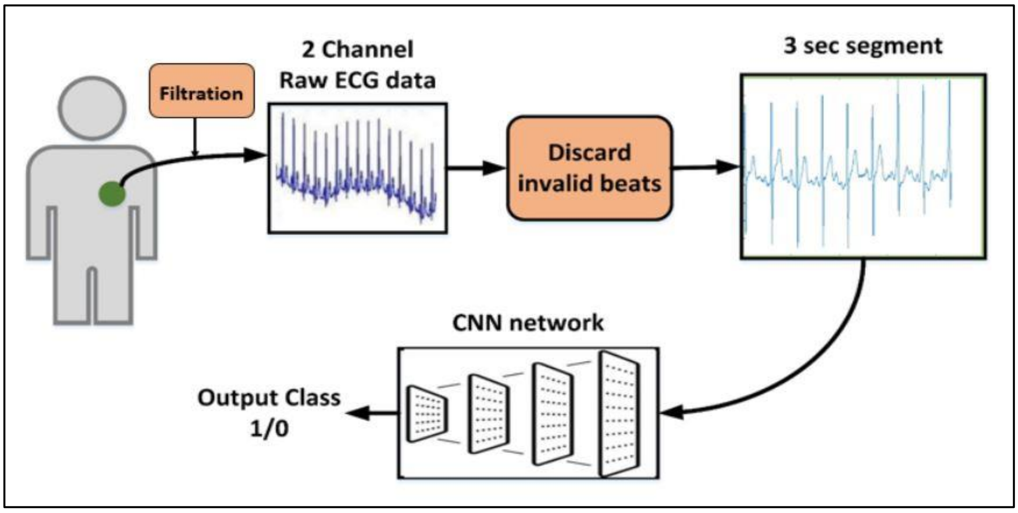

Figure 1. Workflow architecture of proposed method

3.1. Algorithm reviewed

Neural Network with Convolutions A feed-forward neural network is a type of CNN [4]. It is frequently used to categorize photos. CNN is located in the nucleus with biases and weights that can be learned. Each neuron accepts some inputs, performs an integral, and adds nonlinearity if desired [8]. The entire network represents a single variation scoring function, from raw sample data on one endpoint to class scoring on the other, with an activation function on the last (completely connected) layer. CNN represents the input data as multidimensional arrays [9]. It works well for a large volume of labeled data. [12]. A receptive field is created when CNN extracts every portion of the input picture. It provides weights to each neuron depending on the receptive field's relevance in distinguishing the importance of neurons from one another. Convolutional, convolutional, and convolutional layers are common in CNN architecture. fully connected and sigmoid/SoftMax layers [15]. A graphical representation of the CNN model used in this study is presented in Figure 2. This model consists of 4 one dimensional convolutional layers, 3 average pooling layers, 1 Flatten and 2 dense layers:

1. This work employs a one-dimensional convolution kernel to handle a one-dimensional ECG signal, which convolutes independent of the convolution layer of the preceding layer. Mitigating the convolution kernel and passing it to the convolution neural network (CNN yields the convolution layer's output). For all convolutional layers with learning parameter 'alpha' = 0.7 in Eq. 1, the 'LeakyReLU' activation function is utilized. The reality that the ECG signal propagates in both positively and negatively domains is the reason for choosing this function. As a result, as order to catch the signal's true nature, a function is needed to

accommodate both the domains along with the ability of explore the hidden information of the data to recognize its actual nature. Multiple values of this parameter are experimented (between 0 and 1) and 0.7 is found to be the most optimal one. Kernel size is 3 is designated for these layers and 8 filters are used corresponding to 8 representations of the data at each layer to eliminate noises. Figure 3 show the Normal and Abnormal ECG segments. The network is trained with the 'adam' optimizer using a random sample of 1 normal and pathological ECG segment. 'LeakyReLU' is a transfer function for calculating dense layer output. The 'binary cross entropy' loss function is used to perform these operations on each sample of the signal. The model has 3,503,273 total parameters, all of which are trainable.

$$f(x) = \{x \quad x \geq 0\}, \tag{1}$$

$$f(x) = \{\alpha x \quad x < 0\}, \tag{2}$$

2. Flatten Layer: The Flatten layer is a utility layer that flattens an input of 3-dimensional shape to 1 dimensional vector. This vector will be used as input to fully connected layer.
3. Pooling Layer: Typically, the pooling layer is really the convolution of the previous layer. By reducing the size of CNN model output data, network complexity and overfitting are reduced. The network's resilience is improved by this method. The pooling tier collects or optimizes the output features of the convolutional layer, with average filter and peak pooling as related algorithms. In this investigation, average pooling is employed.
4. Fully connected layer: After collecting features from multiple convolution layers and pooling layers, the fully connected (FC) layer is utilized to improve the connectedness of all features. Finally, the FC layer, which contains only one neuron, does a logistic regression classification. The completely connected layer transfers the weighted sum of the previous layer's output to the input signal.

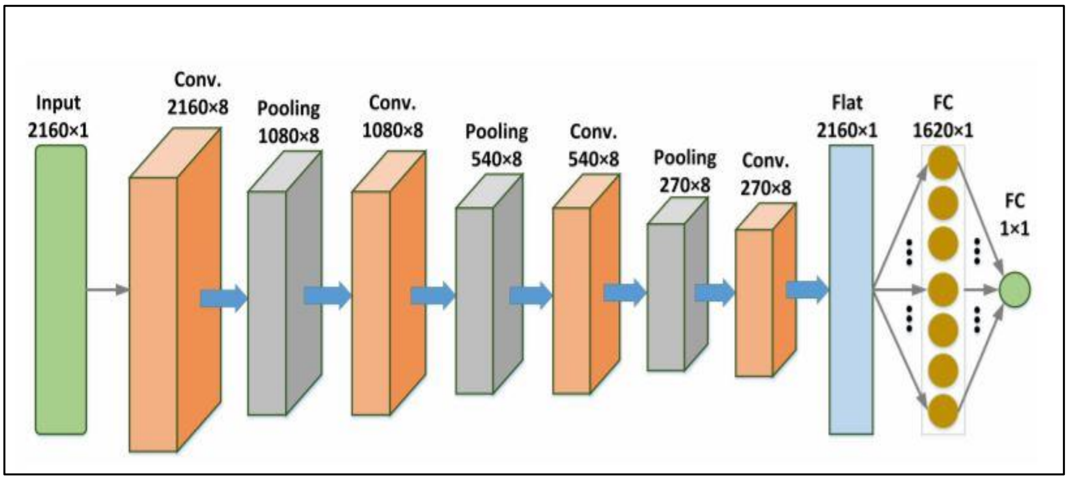

Figure 2. Proposed CNN architecture

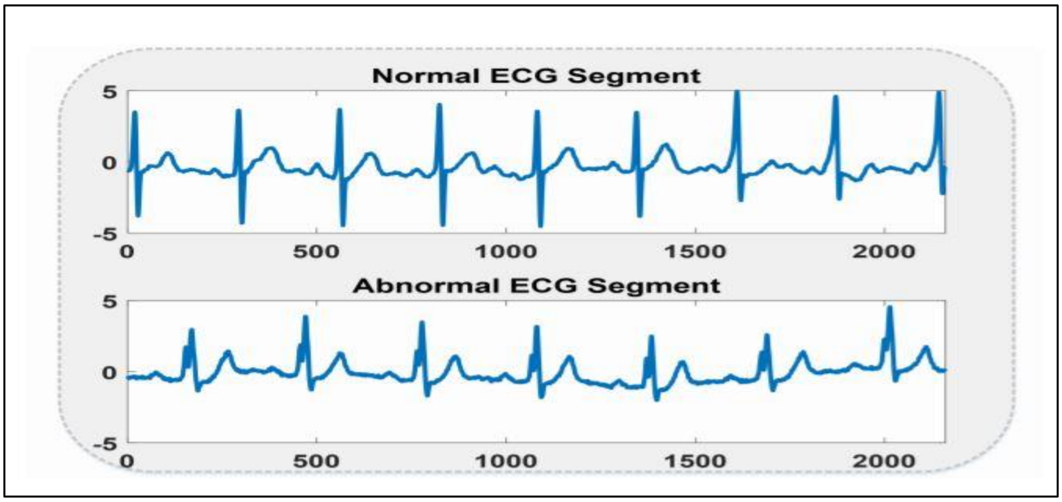

Figure 3. Normal and Abnormal ECG segments

3.2. Experiments setup and data preparation

The proposed ECG signal classification scheme is patient independent; therefore, all the 48 records of the database are processed jointly. After discarding the invalid beats and segmenting the data into 3 sec trials, 2160 samples from 1 segment is obtained. As the dataset includes two ECG electrodes with sampling rate of 360 Hz, therefore, for a 2 sec signal segment 360 × 3 × 2 = 2160 samples are retrieved, while 3 corresponds to segment duration and 2 represents number of ECG electrodes. Hence, to propose using raw ECG signal directly, these segments are directly used as input to the CNN model. The instantaneous frequency and the spectrogram entropy have been used to test feature selection. Figure 4 shows further information about the data for each Arrhythmia ECG signal segment and normal ECG signal fragment amplitude in the network. Figure 5 shows a metric of spectral power distribution by frequency tested. Finally, the instantaneous frequency of arrhythmic and normal ECG is presented in Figure 6.

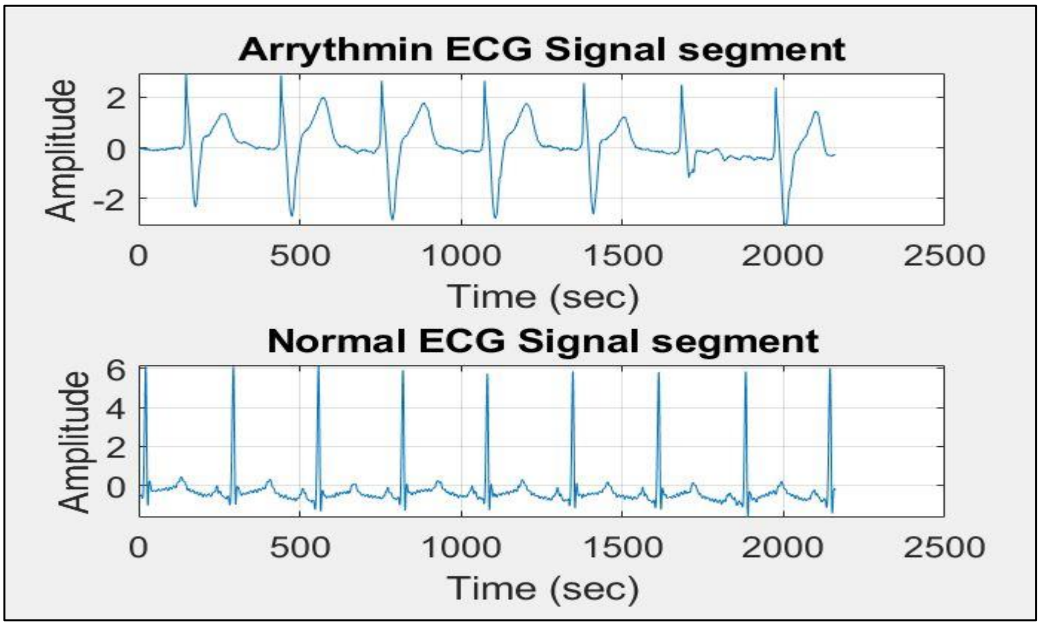

Figure 4. Amplitude chart of ECG signal segment

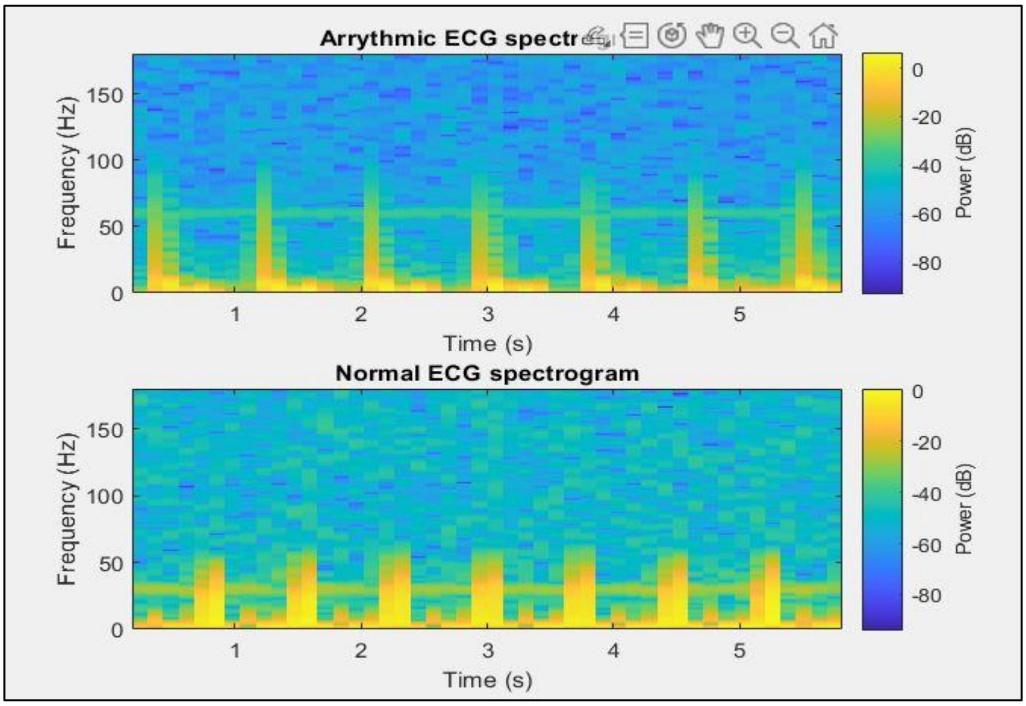

Figure 5. ECG Spectrogram entropy

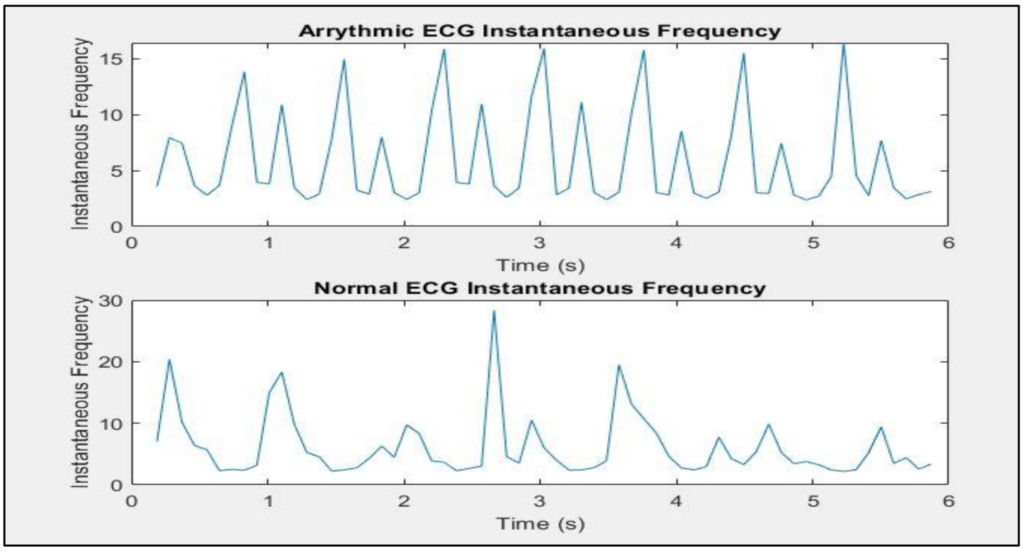

Figure 6. ECG Instantaneous frequency

4. Results and discussion

The CNN model was trained to classify input ECG signals using 82873 randomly selected segments of ECG signals. Thus, we divided the data set into 70% training ratios and 30% test ratios, which were taken into account in the training process performed on MATLAB. Accordingly, as shown in Figure 7, 98% accuracy and 2% loss were found. The final accuracy of normal ECG for the training set was 97.8%, and 98.5 % for arrhythmic ECG was 98.5 %, as shown in Figure 8.

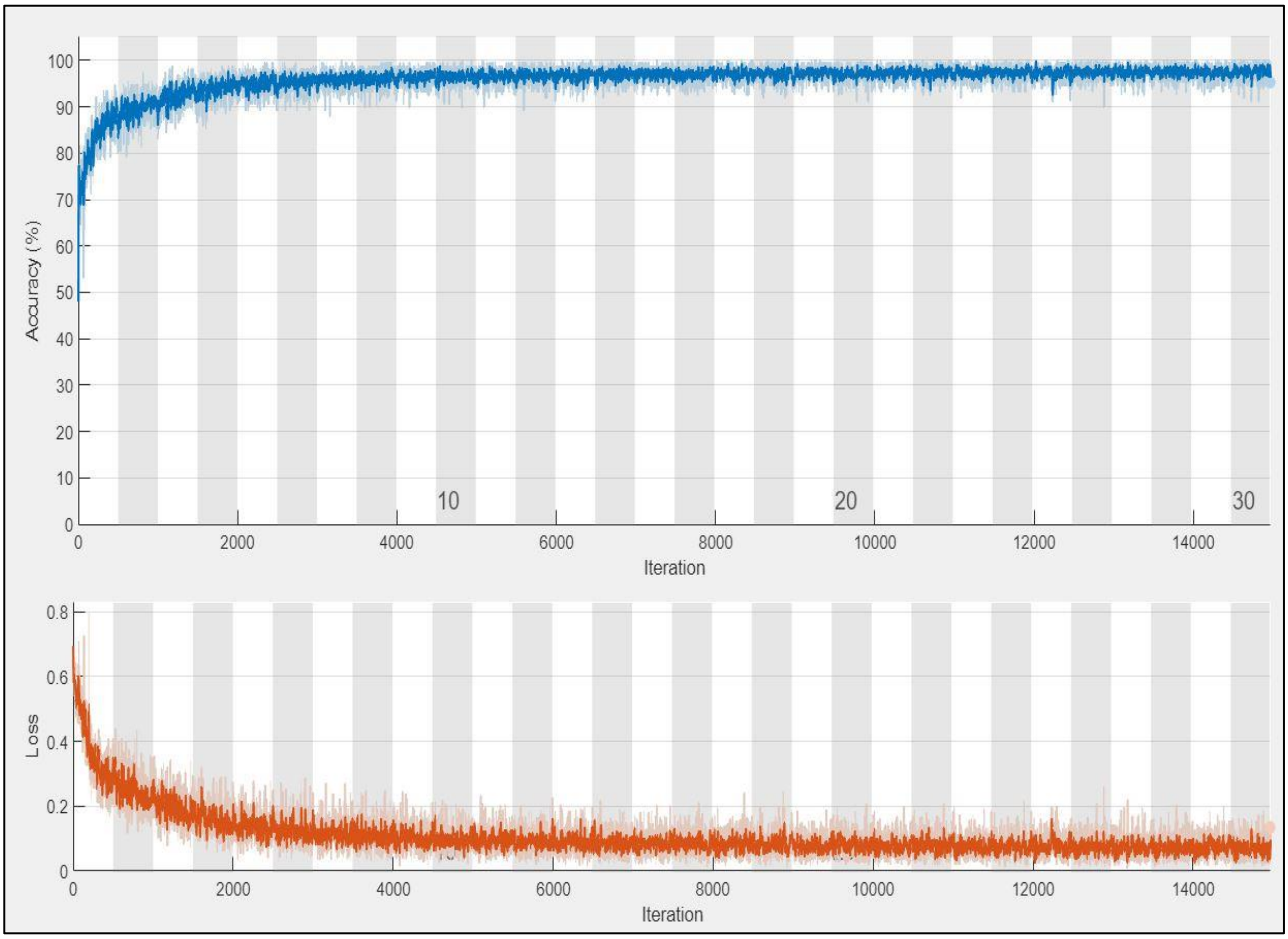

Figure 7. The implementation of Training data for proposed methodology

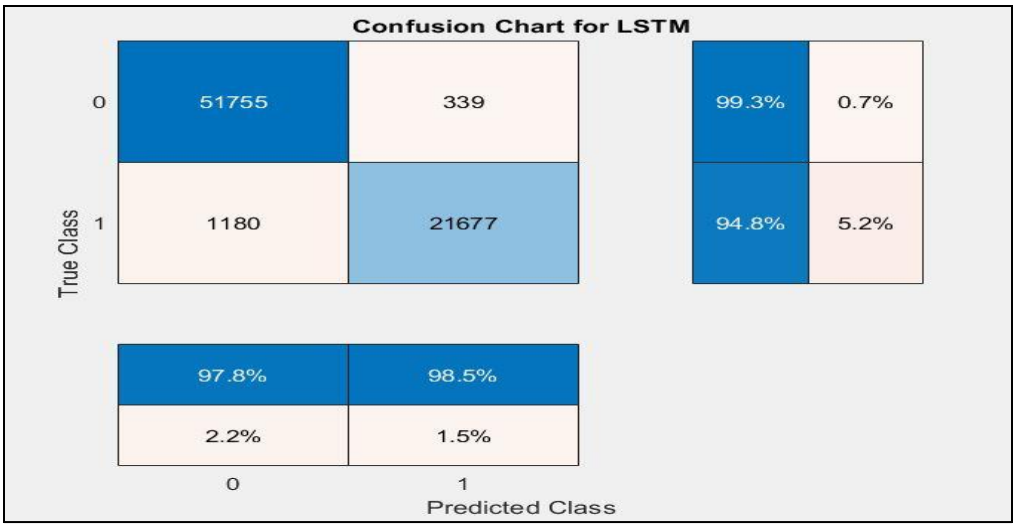

Figure 8. Confusion Chart for LSTM

Test data comprises of 26259 segments in total with 17834 trials are normal beats and remaining are abnormal ones. This study uses the confusion matrix, accuracy (Acc), F1 score, sensitivity (Sen), and specificity (Sp) to more carefully examine and compare the suggested CNN model's classification impacts (Spe). The accuracy rate, for example, indicates the capacity to identify the sample's true condition; the sensitivity, for example, represents the ability to differentiate heart rate; and the specificity, for example, indicates the ability to detect a rate adversely. The corresponding expressions are represented in Eq. (3–6):

$$Acc = (TP+TN) \ / \ (TP+TN+FP+FN) \tag{3}$$

$$Sen = TP / (TP+FN), \tag{4}$$

$$F1 = TP / (TP + ½ \times (FP + FN)), \tag{5}$$

$$F2 = TP/ (TP + 0.8 \times FP + 0.2 FN), \tag{6}$$

$$Spe = TN/(TN+FP), \tag{6}$$

True positives are represented by TP, true negatives by TN, and false negatives and positives by FN and FP, respectively. Table 2 summarizes the accuracy, Feature selection 1 (F1) score, Feature selection 2 (F2) score, sensitivity, and specificity of the proposed ECG signal processing technique for arrhythmia identification using the CNN, SVM, KNN, and Random Forest algorithms. These methods were examined because, as shown in Table 1, they have good correlation accuracy for the AF in the literature. Table 2 shows that the suggested model achieves 98.5 percent accuracy for CNN, 92 percent for KNN, 91 % for SVM, and 88.2 % for the Random Forest method.

Table 2. Classification Performance of the Proposed Methodology for Test Data

ML-DL Algorithm	Accuracy (%)	F1 (%)	F2 (%)	Sensitivity (%)	Specificity (%)
CNN	98.5	99.3	94.8	78	93
SVM	91.2	92.5	91.2	61	83
KNN	92.3	90.2	88.3	71	85
Random forest	88.2	89.3	86.1	74	82

Furthermore, the accuracy rate of the proposed model was as compared to when features are selected as presented in Figure 9. It was found that if the feature selection technique was incorporated in a CNN with conventional layers, a dropout and two fully connected layers, then this will result in a classification accuracy of to 98.5%, whereas without feature selection will result in only in 57.5%. Furthermore, the proposed model has been tested. compared with others in the literature and has shown the highest accuracy as shown below in Table 3. This came upon choosing the best dataset and the best machine learning algorithm, CNN that has applied two feature selections with a high accuracy result. Figure 10 shows a confusion matrix of the acquired data.

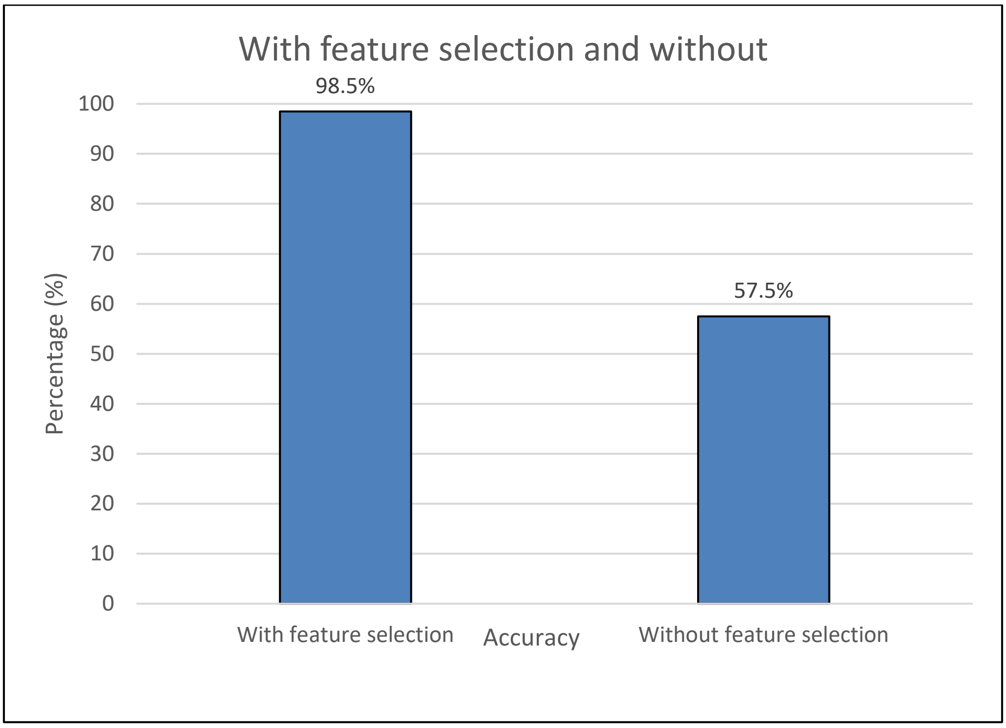

Figure 9. Results of experiment with and without feature selection

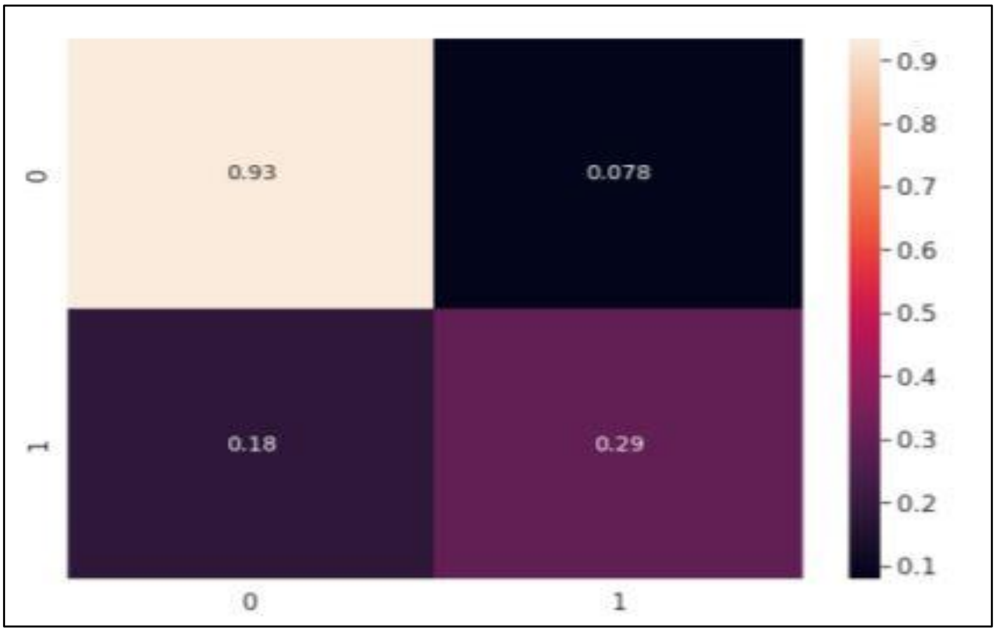

Figure 10. Confusion matrix

Table 3. Citation, Common algorithms, Results, and Common databases

Citation	Common Algorithms	Accuracy Results [%]	Common Dataset
[20]	CNN	90%	Cardiology Department of Nice University Hospital Center (CHU)
[28]	CNN	93.1%	Information Mart for Intensive Care (MIMIC) III dataset
[38]	CNN	92%	MIT-BIH database
[39]	CNN	95%	MIT-BIH database
[40]	CNN	87%	AFIB, MIT-BIH
[59]	CNN	91%	LGE-MRI Patient dataset
[61]	CNN	96%	128-Lead BSPM System dataset
[73]	CNN	94%	MIT-BIH AF
[85]	CNN	94.1%	Korean National Health Insurance Service-National
[88]	CNN	91%	Neurointensive Care Unit at UCSF
[106]	CNN	92%	CinC17DB, StrokeStop I database (SSIDB)
[111]	CNN	95%	ECG data set
Our proposed method	CNN	98.5%	MIT-BIH database

5. Conclusion and future work

The ability of deep neural network models to classify ECG data was thoroughly investigated. Single dimensional CNN model was analyzed to categorize the actual nature of the ECG signal corresponding to normal or abnormal heart rate for detection of the arrhythmia disease. Segments of raw ECG data were combined with feature engineering to produce a genuine representation method for reliable AF detection. In order to produce an optimum model, several network sizes and other relevant functions were used to determine the loss and improve the model. The classification results of the proposed technique were compared to those of current methods. In compared to traditional models, the results showed that incorporating the suggested system model for AF detection yielded a greater accuracy rate. Finally, it is suggested that this paradigm be researched further in the future for prospective adoption to improve diagnostics.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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