Atrial Features-Based Prediction of Sinus Tachycardia Using LSTM-RNN Model

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Abstract

Sinus Tachycardia (ST) reveals pathological dysfunctions and differentiates distinct arrhythmias. The progression of Atrial Fibrillation (AF) from paroxysmal to persistent is frequently associated with tachycardias. Therefore, the study aims to use the Long Short-Term Memory Recurrent Neural Network (LSTM-RNN) model to investigate the influence of atrial characteristics on predicting tachycardia. Electrocardiograms (ECGs) from 10 healthy volunteers 26 ± 3.4 years (4 females) were recorded for Sinus Rhythm (SR) and ST conditions along with 10 AF data. For ST, the 5-day follow-up recording was performed with each volunteer. ECG recordings were performed for a duration of 10 s. Atrial features, along with R-R interval and Heart Rate (HR), were utilized as inputs for the developed LSTM-RNN multivariate time series forecasting model. The features were statistically analyzed before training the LSTM-RNN model. The correlation is positive and significant between HR and atrial amplitude ($p<0.05$) in ST. The developed LSTM-RNN model has training and validation loss with mean squared error values of 0.0827 and 0.1568. Thus, the study concludes that the proposed atrial feature-based LSTM-RNN model may be suitable for predicting AF and effectively distinguishing it from other atrial arrhythmias in the future.

1. Introduction

Tachycardia frequently coexists with the progression of paroxysmal to persistent Atrial Fibrillation (AF) [1]. AF is a prevalent cardiac arrhythmia marked by the rapid and abnormal electrical activity of the atria that can lead to a rapid ventricular response. This higher ventricular rate is mostly inconsistent, thus having irregular R-R intervals. Furthermore, tachycardia is characterized by a sinus rate greater than 100 bpm [2].

Sinus Tachycardia (ST) stands as the most prevalent arrhythmia. However, increased sympathetic activation, circulating catecholamines, and/or reduced parasympathetic effect may make it a normal and beneficial physiological response to physical and psychological stress. [3]. Furthermore, inquiries on ST demonstrate a range of issues, ranging from a persistent autonomic disorder to an underlying inflammatory or other infectious condition [4].

The identification of atrial arrhythmias relies on evaluating the presence and characteristics of P-waves with their temporal changes [5]. Moreover, a thorough examination of P-wave morphology is essential to exclude persistent atrial arrhythmias [4]. Most AF detectors primarily rely on the analysis of R-R interval irregularity, which can lead to false positives diagnoses [6], [7]. However, AF is typically distinguished by the irregular R-R intervals, P-waves disappearance, and the occurrence of fibrillatory waves (*f*-waves).

In a recent study, several atrial features have been incorporated to examine the variations in P-wave morphology during both Sinus Rhythm (SR) and ST settings, with the aim of optimal lead selection [8]. These features comprise P-wave (atrial activity) amplitude, area, duration, duration/amplitude ratio, area/duration ratio, and P/QRS_{pp} ratio. Hence, implementing these atrial features along with R-R interval may increase the prediction and diagnostic accuracy of atrial arrhythmias. Moreover, a study predicted the missing data in electrocardiogram (ECG) signal by a Long Short-Term Memory Recurrent Neural Network (LSTM-RNN) with a low root mean squared error of 0.087 [9]. Hence, the current study also leverages the LSTM-RNN to analyze past features, facilitating the observation and prediction of Heart Rate (HR).

The main aim of this study is to use an LSTM-RNN model to predict HR under ST conditions. The proposed model is based on the concept of multivariate time series forecasting. Furthermore, the LSTM-RNN has a internal gate topology, enabling it to retain and utilize information from past patterns.

2. Methods

2.1. Data collection

ECGs were collected from 10 healthy volunteers for SR and ST conditions under a supine rest position. The

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participants in the study had an average age of 26 ± 3.4 years (4 females). For SR, the volunteers were asked to relax for 1 minute, and the ECG recording was performed for a duration of 10 seconds. Subsequently, ST recording was performed after a 5-minute treadmill exercise for the same duration. On focusing ST, each volunteer underwent a 5-day follow-up with 10-second ST recordings, resulting in 50 data samples for ST, with 5 samples from each volunteer. Additionally, the study included 10 AF data from the Chapman University and Shaoxing People's Hospital (CUSPH) database with a mean age of 76 ± 6.9 years [10]. As a result, 30 different data samples were used for SR, ST, and AF. All the participants were informed about the study and included after proper consent.

2.2. Feature set

The feature set is made only for ST conditions as the study focuses on predicting tachycardia HR. The ECG signal was acquired and processed using the Mindray Beneheart R12 ECG machine to extract the required features. The input feature set consists of atrial features like P-wave amplitude, area, duration, duration/amplitude, area/duration, and P/QRS_{pp} ratio, along with the R-R intervals and HR. The input feature set from the ST condition is used for the design and development of the LSTM-RNN model for predicting tachycardia HR.

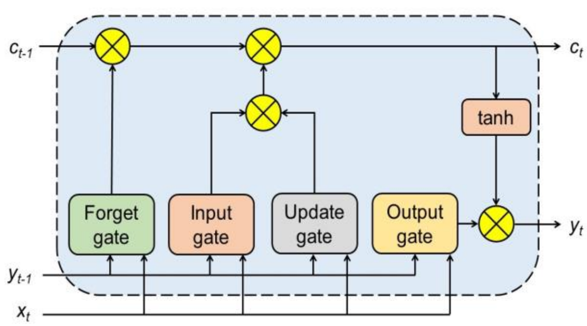

Figure 1. Block diagram of Long Short-Term Memory Recurrent Neural Network (LSTM-RNN). Where 'x_t' is the current state input, 'y_t' is the output gate, 'y_{t-1}' previous state output, 'c_t' upgrade gate, and 'c_{t-1}' is the previous upgrade gate.

2.2. Statistical analysis

The features from SR, ST and AF were subjected to statistical analysis. All the data underwent a Shapiro-Wilk test to assess their normal distribution. Pearson's correlation (r-value) was intended to examine the relationship between HR and atrial amplitudes. Additionally, a Two-Sample T-Test was performed to identify significant differences ($p<0.05$). All data were expressed in mean ± Standard Deviation (SD).

2.3. LSTM-RNN architecture

The LSTM-RNN architecture employs an internal gate design to forecast future sequences for long-term data. Figure 1 depicts the overall block design of the LSTM-RNN, which has four essential gates: forget, input, update, and output. The study [9] details the equations for all the gates and their update of internal weights in training the network. The LSTM-RNN multivariate time series forecasting approach is a sophisticated technique for predicting future values of several features based on their past patterns and correlations. The performance of the developed LSTM-RNN model was assessed using Mean Square Error (MSE).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (1)$$

where 'n' is the number of data points 'y_i' represents the actual values, whereas '$\hat{y}_i$' represents the predictable values.

3. Results

Correlation analysis was made between the HR (bpm) and the atrial amplitudes (μV) for SR, ST, and AF. The atrial amplitudes of SR, ST and AF differ as P-waves (SR and ST) and *f*-waves (AF). Pearson's correlation coefficient has r values of -0.02, 0.35, and 0.39 for SR, ST, and AF, respectively. The correlation was positive for AF and significantly positive for ST ($p<0.05$).

Table 1. Parameters of SR, ST, and AF.

Parameters	SR	ST*	AF*
R-R interval (ms)	764 ± 72.7	527 ± 77.3	693 ± 193.2
HR (bpm)	79 ± 7.6	116 ± 17.1	100 ± 27.6
P/*f*-wave amplitude (μV)	102 ± 8.4	158 ± 38.7	37 ± 17.4

The values are in mean ± SD and *Two sampled T-Test with $p<0.05$ (SR vs ST; SR vs AF).

Table 1 displays the atrial amplitude, R-R interval and HR parameters of SR, ST, and AF. The parameters in ST and AF have significant differences ($p<0.05$) from SR. The mean HRs in ST and AF are 116 and 100 bpm. Table 2 shows the HR and R-R interval along with the atrial features of the study population among SR and ST groups. The parameters of ST in analyzing HR also

Table 2. Atrial (P-wave) features and HR for SR and ST conditions.

Parameters	SR	ST	p-value*
HR (bpm)	79 ± 7.6	116 ± 17.1	p<0.05
R-R interval (ms)	764 ± 72.7	527 ± 77.3	p<0.05
amplitude (μV)	102 ± 8.4	158 ± 38.7	p<0.05
duration (ms)	97 ± 15.4	102 ± 17.3	p>0.05
area (μV*ms)	5843 ± 1521	8940 ± 3110	p<0.05
area/duration (μV)	60 ± 14	86 ± 23.3	p<0.05
P/QRS_{pp}	0.1 ± 0.05	0.09 ± 0.03	p>0.05
PR interval (ms/μV)	0.9 ± 0.3	0.6 ± 0.1	p<0.05

The values are in mean ± SD and *Two sampled T-Test.

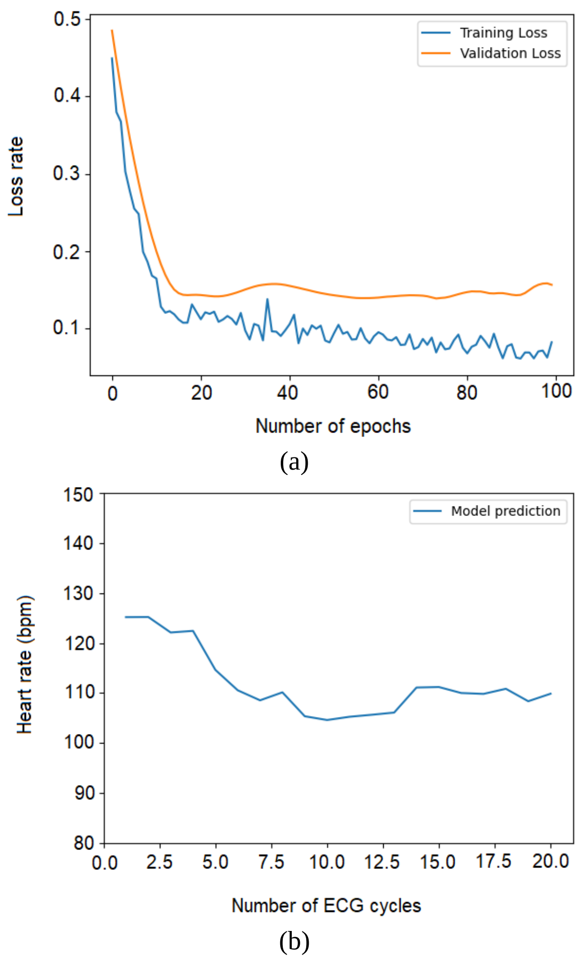

Figure 2. (a) LSTM-RNN model's loss curve with training and validation losses and (b) Output of the model prediction with mean heart rate of 112 bpm.

depended on atrial features. The features other than the P/QRS_{pp} ratio and P-wave duration have significant differences among the ST and SR groups.

Figure 2(a) illustrates the loss rate of the training and validation of the LSTM-RNN model. The plot displays the number of epochs, and the loss rate (MSE) in its x and y-axis. The training loss is recorded as 0.0827, while the validation loss is 0.1568. In Figure 2(b), the LSTM-RNN model's forecast of the ST volunteer's HR is presented. The plot shows the number of ECG cycles, and the HR (bpm) in its x and y-axis. The mean value of the predicted HR is 112 bpm.

4. Discussion

The primary outcomes obtained from this study were the prediction of tachycardia using atrial features along with the R-R intervals. Tachycardia has an influence on the conversion from paroxysmal to persistent AF [11]. Thus, a study on tachycardia may be useful for predicting this transition in AF applications among pacemaker patients. Prolongation of tachycardia in paroxysmal AF patients was a significant indicator for early estimation of AF conversion. The study findings show that the mean HR from AF was about 100 bpm which is more of an ST condition (HR = 116 bpm), as shown in Table 1. Therefore, tachycardia is not only pathological but also a significant predictor for AF. From a syllogistic standpoint, it is hypothetically plausible that people with tachycardia are more susceptible to developing persistent AF.

The development of AF is influenced by atrial remodeling [12]. Thus, the atrial features-based prediction will give more insights into the prediction of tachycardia. Moreover, the physiologically induced ST has a significant correlation (p<0.05) between HR and P-wave amplitude in the proposed study. Generally, R-R intervals will have significant differences between the ST and SR groups. Additionally, in the current study, the atrial features also have significant differences, as reported in Table 2. Therefore, the study suggests that the prediction of tachycardia in AF may be improved by these features.

Several predictors have been postulated for detecting the progression of AF [13]. The present investigation employed atrial features in addition to R-R intervals for predicting tachycardia. The present study is a preliminary work to investigate the atrial features like area, area/duration, P/QRS_{pp} ratios etc., for predicting tachycardia conditions. Tachycardia has a significant chance of progressing to persistent AF when it is pathological. However, prediction models such as the LSTM-RNN that were developed may be able to make an impact on clinical decision-making in predicting AF through tachycardia. The designed multivariate time series forecasting-based LSTM-RNN model provides the best prediction of tachycardia HRs, with MSEs in training and validation of 0.0827 and 0.1568, respectively.

Moreover, the predicted ST volunteer's HRs were in tachycardia condition by having a mean rate of 112 bpm.

The present study's limitation is the careful exclusion of hospitalized patients with any cardiac abnormalities and includes only the physiologically induced tachycardia conditions from the healthy cohorts. However, we were still unable to examine the possibility of the same results in the patients. Nevertheless, we tested the coexistence of tachycardia in the AF by including some of the population from the CUSPH database. Finally, the current investigation becomes more retrospective.

5. Conclusion

The present work predicts tachycardia using the atrial features-based LSTM-RNN model with the training and validation MSE of 0.0827 and 0.1568. The logic implemented in the LSTM-RNN model is multivariate time series forecasting. Therefore, this study may help to delineate the prediction of AF using the atrial-based features along with the R-R interval and HR using LSTM-RNN models in future. The key benefit of using the LSTM-RNN model is that it predicts missing data effectively, which may minimize false-negative predictions of other arrhythmias.

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