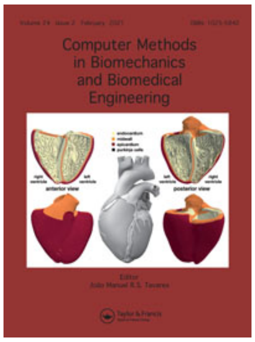

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Classification of normal sinus rhythm, abnormal arrhythmia and congestive heart failure ECG signals using LSTM and hybrid CNN-SVM deep neural networks

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ABSTRACT
Effective monitoring of heart patients according to heart signals can save a huge amount of life. In the last decade, the classification and prediction of heart diseases according to ECG signals has gained great importance for patients and doctors. In this paper, the deep learning architecture with high accuracy and popularity has been proposed in recent years for the classification of Normal Sinus Rhythm, (NSR) Abnormal Arrhythmia (ARR) and Congestive Heart Failure (CHF) ECG signals. The proposed architecture is based on Hybrid Alexnet-SVM (Support Vector Machine). 96 Arrhythmia, 30 CHF, 36 NSR signals are available in a total of 192 ECG signals. In order to demonstrate the classification performance of deep learning architectures, ARR, CHR and NSR signals are firstly classified by SVM, KNN algorithm, achieving 68.75% and 65.63% accuracy. The signals are then classified in their raw form with LSTM (Long Short Time Memory) with 90.67% accuracy. By obtaining the spectrograms of the signals, Hybrid Alexnet-SVM algorithm is applied to the images and 96.77% accuracy is obtained. The results show that with the proposed deep learning architecture, it classifies ECG signals with higher accuracy than conventional machine learning classifiers.

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KEYWORDS
Electrocardiography; normal sinus rhythm; arrhythmia; congestive heart failure; LSTM; CNN

1. Introduction

Electrocardiogram (ECG) analysis has been established at the center of the diagnosis of cardiovascular pathology since its development in the twentieth century. ECG signals reflect the electrical activity of the heart. Therefore, changes in the heart rhythm disturbances or ECG waveform are evidence of underlying cardiovascular problems such as arrhythmias. The signal is based on the standard 12-lead electrocardiogram that measures electrical potential from 10 electrodes located in different parts of the body surface, six chest and four limbs. It is important to obtain and monitor ECG signals for early diagnosis of diseases such as Arrhythmia and CHF. The rapid development of computer technology has enabled improvements in data collection and computer-aided diagnostic methods. Thanks to these developments, the detection of heart conditions has become easier.

Current arrhythmia classification techniques report low accuracy for several classes of arrhythmias due to class conflict and class imbalance problems. Arrhythmias are divided into five classes: ANSI/AAMI EC57: non-ectopic beat (N), supraventricular ectopic beat (S), ventricular ectopic beat (V), fusion beat (F) and unknown beat (Q) according to 2012 (AAMI 2012). Algorithms used for arrhythmia classification include preprocessing, feature extraction, and classification. Classification becomes complicated when class conflict and class imbalance problems occur together.

Singh et al. proposed a model for the diagnosis of cardiac arrhythmias. In three different machine learning methods applied on the Cardiac Arrhythmia data set, three filter-based feature selection methods were applied and the best features were selected. Feature selection is an important preprocessing step to identify effective factors in the diagnosis of patients suffering from arrhythmia. Thus, it is possible to identify the underlying health factors for the heart-related deaths. SVM, random forest and JRip were used to analyze the performance of feature selection methods. The highest accuracy of 85.58% was achieved with the random forest classifier (Singh and Pradeep 2018). Isin et al. proposed a deep learning-based method to

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classify patient ECGs according to the relevant cardiac conditions and perform automatic ECG arrhythmia diagnosis. In the method, Alexnet is used as a feature extractor. The extracted features are given to a simple back propagation neural network to achieve the final classification. Three different ECG waveforms were selected from the MIT-BIH Arrhythmia database to evaluate the proposed method. The main focus of the study is to apply a simple, reliable and easily applicable deep learning technique to classify three different cardiac conditions. The results show that it can achieve very high performance rates with the deep learning feature that is gradually transferred with a traditional back propagation neural network. While the highest rate of accurate recognition obtained was 98.51%, test accuracy was around 92% (Isin and Ozdalili 2017). Bulbul et al. used MLP (Multilayer Perceptron) and SVM (Support Vector Machine) techniques to classify P, Q, R, S, T waves in ECG signals with machine learning techniques. In the study, BP (Back Propagation) algorithm with MLP classifier and K-A (Core-Adatron) algorithm with SVM classifier were preferred. In addition, wave transformation techniques such as DWT, DCT and CWT have been used to increase the success of the classification used in the study (Bulbul et al. 2017). Alarsan et al. proposed an ECG classification approach using machine learning based on various ECG features. These features are inputs of the machine learning algorithm and a 205,146 data was used to evaluate the performance of the classification. Machine learning libraries and Decision Tree, Random Forests, Gradient-Boosted Trees (GDB) algorithms were used for classification. The proposed method has been evaluated in the initial MIT-BIH Arrhythmia and MIT-BIH Supraventricular Arrhythmia database. The results showed that the approach achieved an overall accuracy of 96.75% using the GDB Tree algorithm and 97.98% using random Forest for binary classification. For multi-classification, 98.03% accuracy was achieved using Random Forest (Alarsan and Younes 2019).

Mustaqeem et al. proposed the SVM algorithm for the classification of Arrhythmia subtypes. Support vector machine for multi-class classification with One-Against-One (OAO), One Against-All (OAA) and error correction code (ECC) to detect the presence and absence of arrhythmias based approaches were used. The performance of the classifiers was evaluated using accuracy, kappa statistics and mean square root error, and the evaluated accuracy was 92.07% (Mustaqeem et al. 2018). Vishwa et al. proposed an automated Artificial Neural Network based classification system for cardiac Arrhythmia using multichannel ECG recordings. They used the neural network model with back propagation algorithm to separate Arrhythmia cases into normal and abnormal classes. Network models are trained and tested for MIT-BIH Arrhythmia. Different structures of ANN are trained with a mixture of data patient Arrhythmia and non-Arrhythmia. Classification performance was evaluated by sensitivity, specificity, accuracy, mean square error (MSE), receiver operating characteristics (ROC), and area under the curve (AUC). Experimental results provide 96.77% accuracy in the MIT-BIH database and 96.21% accuracy in the database prepared by including the NSR database (Vishwa et al. 2011). Rajput et al. proposed a deep neural network-based classifier to detect arrhythmias by converting one-dimensional ECG time series data into multidimensional representation in 2D images. The simulation results on the test database showed an outstanding classification performance compared to other available methods and manual statements by certified cardiologists, and the effectiveness of the proposed method was emphasized (Rajput et al. 2019). Salem et al. used transfer learning to define and classify the four ECG patterns. It has been shown that feature maps learned in a deep neural network trained on a large amount of input images can be used as general descriptors for ECG signal spectrograms and result in features that enable the classification of Arrhythmia. In general, around 7000 samples were subjected to ten-fold cross-validation, with 97.23% accuracy (Salem et al. 2018). Pomprapa et al. proposed automatic classification of arrhythmia by monitoring it for some time in various sitting scenarios, such as the electrical activity of the heart, hospital, home or travel. They used a diagonal wavelet filter bank and a convolutional neural network to classify ECG signals based on normal, left and right bundle branch block and early ventricular contraction. An average of 99.2% sensitivity was achieved using the standard MIT-BIH database (Pomprapa et al. 2019). Zheng et al. developed a classification method for Arrhythmia based on the combination of CNN and LSTM to diagnose eight ECG signals, including normal sinus rhythm. The ECG data used in the study were obtained from the MIT-BIH arrhythmia database. The experimental method mainly consists of two parts. The input data of the model are two-dimensional grayscale images converted from one-dimensional signals. The detection and classification of the input data was carried out using the combined model. The advantage of this method is that it does not require feature extraction or noise filtering on the ECG signal. Experimental results showed high classification performance of the applied method in terms of accuracy, specificity and sensitivity equal to 99.01%, 99.57% and 97.67%, respectively (Zheng et al. 2020). Kim et al. proposed a new Arrhythmia classification algorithm using fast learning and high accuracy Morphology Filtering, Principal Component Analysis and Extreme Learning Machine (ELM). The proposed algorithm classifies six beat types: normal beat, left bundle branch block, right bundle branch block, premature ventricular contraction, atrial premature beat, and paced beat. Experimental results of the entire MIT-BIH Arrhythmia database show that the proposed algorithm's performances are 98% for average sensitivity, 97.95% for average specificity and 98.72% for average accuracy (Kim et al. 2009).

Son et al. examined the power of differentiation of 72 variables and the risk factor of Pro Brain Natriuretic Peptides (Pro-BNP) in distinguishing patients with congestive heart failure (CHF) from dyspnea patients. In the study, coarse clusters and logistic regression were used to reduce the property area. Then, a decision tree based classification produced by the feature set was implemented in the previous step. Experimental results are 97.5% sensitivity, 97.2% specificity, 97.7% positive predictive value 97.2%, negative predictive value 97.7% and ROC curve 97.5% of the coarse cluster decision making model. The accuracy for the logistic regression decision model is 88.7%, sensitivity 90.1%, specificity 87.5%, positive predictive value 85.3%, negative predictive value 91.7% and ROC 88.8% (Son et al. 2012). Chen et al. proposed a deep learning approach that combines convolutional neural networks (CNN) and long short-term memory networks (LSTM) to automatically identify six types of ECG signals. Classification of normal (N) sinus rhythm segments, atrial fibrillation (AFIB), ventricular bigeminy (B), pacing rhythm (P), atrial flutter (AFL), and sinus bradycardia (SBR) ECG signals for two databases 99.32% and 97.15% was carried out with accuracy (Chen et al. 2020). Oh et al. proposed an automated system based on convolution neural network (CNN) and long-term memory (LSTM) for the diagnosis of normal sinus rhythm, left bundle branch block (LBBB), right bundle branch block (RBBB). Atrial premature beat (APB) and early ventricular contraction (PVC) in ECG signals. The novelty of this study is the use of variable length ECG signals. Classification accuracy, sensitivity and specificity values of the proposed system were 98.10%, 97.50% 98.70%, respectively (Oh et al. 2018). Swapna et al. proposed CNN-LSTM method in distinguishing normal and abnormal (cardiac arrhythmia) ECG. The accuracy parameter was 0.834 with five-fold cross validation (Swapna et al. 2018). Sangaiah et al. proposed An intelligent learning approach by extracting features from ECG signals for arrhythmia analysis. The proposed method is based on the Hidden Markov Model (HMM). Feature extraction and feature selection were performed from ECG signals and 5 different arrhythmia types were classified. HMM classifier was an average accuracy of 99.8% in classifying the samples into five types of arrhythmia (Sangaiah et al. 2020). Wang et al. proposed a dual fully-connected neural network model for accurate classification of heartbeats. Two-step process was used for classification of normal beats (N), supraventricular ectopic beats (S), ventricular ectopic beats (V), fusion beats (F), and unknown beats (Q) ECG signals. First, 105 features were obtained from the signals. Second, a two-layer classifier is used. Generally, classification was performed with an accuracy of over 90% (Wang et al. 2020). Sharma et al. used the LSTM model to classify ECG signals. First, RR-interval sequences were calculated from ECG signals. Then, the property vector was obtained from the RR interval sequences by Fourier-Bessel (FB) expansion. The vectors obtained are classified with the LSTM model. For classification, the MIT-BIH Arrhythmia Data Set was used and accuracy was achieved 90.07% with ten-fold cross validation (Sharma et al. 2020). Masetic et al. implemented a classifier using features extracted from the ECG of 13 normal 15 CHF patients. They achieved high accuracy with Random Forests, SVM, C4.5, ANN, k-NN methods (Masetic and Subasi 2016). Isler et al. used heart rate variability (HRV) analysis to distinguish patients with systolic congestive heart failure (CHF) from patients with diastolic CHF. The nearest neighbor and multi-layer perceptron (MLP) was used to evaluate their performance of discriminating between these two groups. The results show that using both data and heart rate normalizations improves classifier performance. With the MLP classifier, they achieved maximum accuracy of 96.43% (Isler 2016). Hussain et al. proposed an automated system to capture temporal, spectral and complex dynamics and analyze HRV signals by extracting multimodal features. Machine learning techniques such as linear, Gauss, radial, and polynomial-based kernel and (SVM), decision tree (DT), k-nearest neighbor (KNN), and community classifiers have been used. Performance was evaluated in terms of specificity, sensitivity, positive predictive value (PPV), negative predictive value (NPV) and area under the recipient study characteristic curve (AUC). The highest performance was achieved with SVM (linear kernel with accuracy = 93.1%, AUC = 0.97, ensemble subspace discriminant with accuracy = 91.4%, AUC = 0.96, and Gauss core accuracy = 90.5%, AUC = 0.95 (Hussain et al. 2020).

In this paper, Alexnet-SVM hybrid structure is proposed for classification of Arrhythmia, CHF and NSR ECG signals. To show the superiority of the proposed method, it was compared with classical machine learning algorithms SVM and KNN algorithms and LSTM. The contribution of this paper to the literature can be summarized as follows.

- Arrhythmia, CHF and NSR ECG signals are classified together.
- Classification was implemented using the Alexnet-SVM hybrid structure.
- The method does not require extra feature extraction or noise filtering to be applied to the ECG signal.
- 96.77% accuracy was achieved.

The rest of the article is organized as follows.

In the second part, information is given about the ECG data used. In Chapter 3, Arrhythmia, CHF and NSR ECG signals and their definitions are presented. In the fourth chapter, SVM, KNN, LSTM definitions and classification results are given. In addition, the classification results are presented by detailing the method proposed in this section. In the fifth chapter, the results are discussed with the literature to show the superiority of the method proposed. The conclusion of the article is presented in the last section.

2. Data

In this paper, three ECG signals, Arrhythmia, Normal Sinus and Congestive Heart Failure are studied. A total of 162 ECG signals are analyzed. 96 of them are used for Arrhythmia, 30 of them are Normal Sinus and 36 of them were CHF signals. MIT-BIH Arrhythmia Database taken from Physio.Net is used for arrhythmia data (MIT-BIH 2020). The MIT-BIH Arrhythmia Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory. A total of 96 of these signals are included in the system as Arrhythmia. The following database is used for the normal sinus rhythm wave. The used database includes 18 long-term ECG recordings of subjects referred to the Arrhythmia Laboratory at Boston's Beth Israel Hospital (now the Beth Israel Deaconess Medical Center). Subjects included in this database are found to have had no significant arrhythmias; they include 5 men, aged 26 to 45, and 13 women, aged 20 to 50. 30 of these signals are processed. For the CHF signal, 36 CHF signals are received from the following database. This database includes long-term ECG recordings from 15 subjects (11 men, aged 22 to 71, and 4 women, aged 54 to 63) with severe congestive heart failure (NYHA class 3–4) (Baim et al. 1986).

Three of these signals are evaluated together and subjected to classification. An example for Arrhythmia, Congestive Heart Failure and Normal Sinus Rate ECG signals are given in Figure 1.

3. ECG and definitions

Electrocardiography (ECG) is often used to identify rhythm disturbances on heart. The ECG creates a graphical record of the heart's electrical beats. For the ECG to be performed, the healthcare worker places small bands called electrodes on the arms, legs and chest. By making different combinations of these electrodes, different records are taken regarding the electrical activity of the heart and recorded on the computer or on paper. Doctors check the shapes and sizes of the waves, the time between the waves, the heart rate, and whether the heartbeat is regular. This test gives important information about the heart and the rhythm of the heart. However, it only shows rhythm disturbances occurring during the procedure. In the sinus rhythm, there are six separate waves (symbolized by the letters P, Q, R, S, T, and U) during a beat of the heart, and they occur in certain order, duration, and dimensions. Although there is a large range in which changes in the heart rhythm are considered normal, more than a certain amount of deviations from the sinus rhythm may be indicative of heart conditions. Normal sinus rhythm, standard waves, segments and ranges in the ECG signal are as in Figure 2.

Congestive Heart Failure (CHF), also known as CHF Heart Failure, occurs when the back of the blood accumulates back into the body, especially the liver, lungs, hands and feet, as the heart can no longer pump blood efficiently. If blood accumulates backwards from the right side of the heart (blood returning from the body to the right side of the heart), the symptoms that typically begin with the swelling of the feet and ankles worsen when the patient is standing

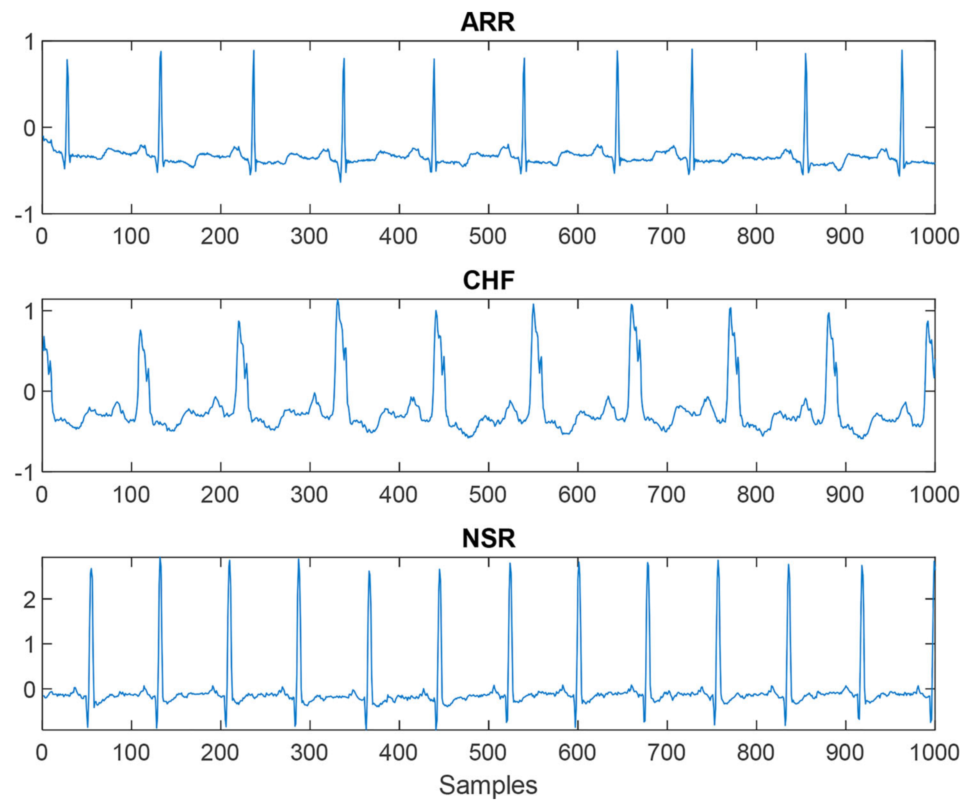

Figure 1. Sample of Arrhythmia, Congestive Heart Failure and Normal Sinus Rate ECG signals (Baim et al. 1986).

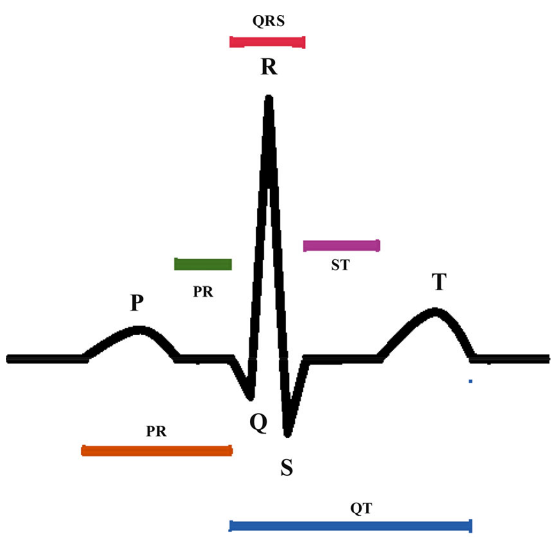

Figure 2. Components of ECG signals.

and passes when they lie down. If the blood coming from the lungs back to the left heart cannot be pumped and accumulates backwards, it can cause shortness of breath and cough, especially during exercise (such as climbing stairs) or while lying down. Many people with heart failure will have signs of disease associated with backward blood accumulation from both the right and left side of the heart.

Arrhythmia (Heartbeat Disorder) is the result of the electrical activity of the area called the sinus node. It causes your heart to beat very fast, very slowly or irregularly as a result of the electrical impulses regulating the heart beats not working properly. This condition is called arrhythmia. Arrhythmia can occur in ways such as the heart running faster, slower, or irregularly than usual. The pulse rate, which is normally 60–100 per minute, can exceed 100 and/or become irregular. When the heart fails to deliver enough blood to the body during a rhythm disorder, a person may experience shortness of breath, fainting, and fainting, and sudden death. Therefore, accurate detection of this heart condition is important.

Normal sinus rhythm is when the stimulus exits the sinoatrial node and reaches the ventricles by following normal physiological pathways. In order for a rhythm to be defined as a normal sinus rhythm, it must meet the following conditions.

Speed: should be between 60 and 100/min.

Rhythm: Should be regular. R-R and P-P distances must be equal.

P Wave: Must have P Waves, P wave width should be 0.04 sec–0.12 sec (1–3 small squares), Amplitude should be maximum 0.25 millivolts (2.5 small squares) and QRS complex response to all p waves.

PR distance: Should be less than 0.20 sec.

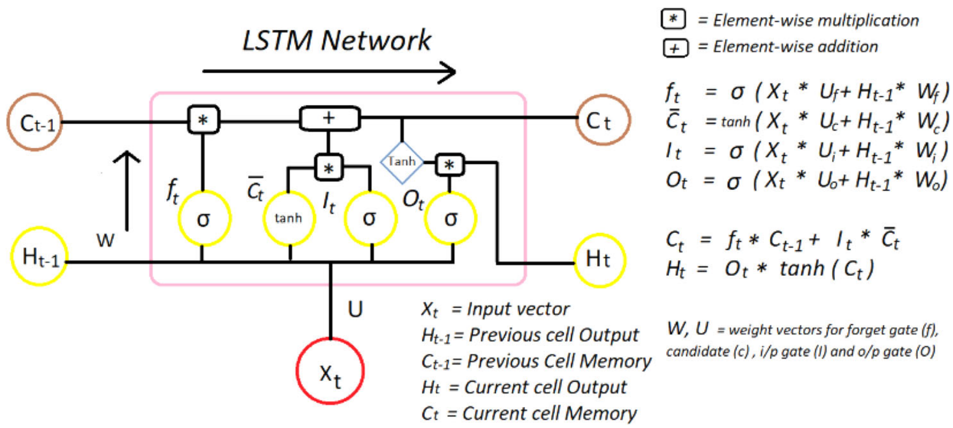

Figure 3. LSTM module structure.

QRS complex: Should be less than 0.10 sec.
PR segment and ST segment: It should be on an isoelectric line.
QT distance: should be normal. (In Women: 0.39 sec. In Men: 0.44 sec.)
T Wave: Expected to be in the same direction as QRS. Its duration is 0.10–0.25 seconds. T wave D1 is positive between D2 and V3-V6, and AVR and V1 are negative. The amplitude of the T wave should be less than 5 mm (0.5 mv) in limb leads and 15 mm (1.5 mv) in chest leads (Park et al. 2013; Sangaiah et al. 2020).

4. Arrhythmia, congestive heart failure and normal sinus rhythm classification

In this paper, three different classifications were carried out for the classification of Arrhythmia, Congestive Heart Failure and Normal Sinus rhythm ECG signals. First, raw ECG signals were classified using classical machine learning algorithms SVM and KNN. Secondly, raw ECG signals are classified with the help of LSTM algorithm, a special type of RNN that can learn long-term dependencies. As the classification performance of these algorithms could not reach the success levels desired by the doctors and the discrimination feature was low, CNN-based classification was last performed. Alexnet, one of the Pre-trained CNN architectures, was used in this classification process. The hybrid Alexnet-SVM architecture, modified using SVM instead of the softmax classification layer of Alexnet architecture, was used for classification. For this purpose, raw signals were converted into spectrogram images and the features extracted from these images was obtained by help of Alexnet. The obtained feature vectors were classified with SVM.

4.1. SVM and KNN classification

In SVM, it makes a class separation by drawing a boundary between two sets of data on a plane for classification (Toraman et al. 2019). Planes are determined for class decision. They are effective when the number of SVM classifier sizes that are effective in high-dimensional spaces is more than the number of samples.

The k-Nearest Neighborhood (k-NN) algorithm is one of the easy-to-implement supervised learning algorithms (Park et al. 2013). Although it is used for solving both classification and regression problems, it is mostly used in the industry for the solution of classification problems. The algorithm makes the classification by using the data in a sample set with certain classes. The distance of the new data to be included in the data set is calculated according to the existing data and the k close neighborhoods are checked. k is a positive integer, typically small. If $k = 1$, the object is assigned to the class of the nearest neighbor. Euclidean, Manhattan and Minkowski functions are generally used for distance calculations.

The raw ECG signals were given as input to SVM and KNN algorithms given briefly, and the accuracy value was obtained as 68.75% and 65.63%, respectively.

4.2. LSTM classification

Long short-term memory is an artificial repetitive neural network (RNN) architecture used in deep learning. Unlike standard feed forward neural networks, LSTM has feedback links. It can process not only single data points (such as images) but also entire data series (such as speech or video). LSTM models consist of three different components or doors (Figure 3).

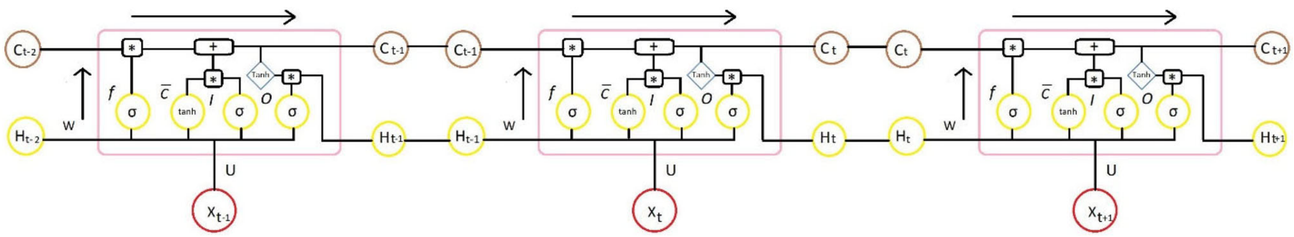

Figure 4. The full architecture of Long Short Term Memory (LSTM) cell.

LSTM cell takes the previous memory state C_{t-1} and does element wise multiplication with forget gate (f);

$$\mathrm{C_t = C_t - f_t} \tag{1}$$

If forget gate value is 0 then previous memory state is completely forgotten.

If forget gate value is 1 then previous memory state is completely passed to the cell (Remember f gate gives values between 0 and 1).

Now with current memory state C_t we calculate new memory state from input state and C layer.

$$\mathrm{C_t = C_t + \left(I_t * C_t'\right)} \tag{2}$$

C_t = Current memory state at time step t^{th} and it gets passed to next time step.

There is an entrance door, an exit door and a forgetting door. LSTMs, very similar to RNNs, take into account inputs from the previous time step when changing the model's memory and input weights. The entrance gate decides which values are important and must be allowed through the model. A sigmoid function is used at the entrance gate, which determines which values are transferred from the repeating network. Here, a TanH function is also used, which decides how important the input values are from -1 to 1 for the model. After considering current inputs and memory status, the output gate decides which values to push to the next time step. At the exit gate, the values are analyzed and an importance ranging from -1 to 1 is given. This organizes the data before proceeding to the next time step calculation. Finally, the job of the forgetting gate is to leave the information it deems unnecessary to decide on the nature of the input values of the model. The forgetting gate uses the sigmoid function on the values and extracts numbers from 0 (forget this) to 1 (hide this) (Figure 4).

In this paper, LSTM architecture consisting of 7 layers and given in Table 1 is used for classification of Arrhythmia, CHF and NSR ECG signals. An ECG signal consisting of 65535 samples is divided into windows of 771 values and given as an introduction to LSTM architecture. So there are 771 hidden units in the first LSTM layer. In the second LSTM layer, there are a total of 1542 hidden units and drop out was selected as 50%.

It is well-known that Accuracy, Precision, Sensitivity and F1_Score parameters obtained from confusion matrix parameters are used to evaluate classification algorithms. Descriptions of the parameters are given in Table 2. The Confusion matrix obtained according to the classification performed with the proposed LSTM architecture is given in Table 3. Overall accuracy obtained in accordance with Figure 5(a) is 90.67%. According to Table 3, ECG signals of NSR class are classified with high success. However, detection of heart conditions is more important than NSR. Therefore, even though LSTM performance is over 90%, it is far from an acceptable result. Figure 5(b) shows LSTM accuracy change.

4.3. Alexnet-SVM classification

One of the main problems of Alexnet architecture is the non-transparency in the intermediate layers during the overall classification procedure, which makes the training process difficult to observe. Another problem refers to the robustness and discriminative ability of the learned features, especially in the latter layers of the network, which can significantly influence the performance. Considering these problems, classical classification algorithms can be used instead of the classification layer of Alexnet architecture to increase the performance in classification problems. In this article, Alexnet-SVM architecture shown in Figure 6 is used for classification of Arrhythmia, CHF and NSR ECG signals. The last pooling layer of Alexnet architecture contains the properties of the images. The softmax layer applied after this layer is removed and SVM classification algorithm is placed instead. Thus, the properties of an image given to the Alexnet entry in the pooling layer are given to the SVM algorithm and the classification is performed. The feature vector given to the SVM input is the

Table 1. Proposed LSTM architecture.

Analysis Result				
Layer	Name	Type	Activations	Learnables
1	Input Layer Sequence input with 771 dimensions	Sequence Input	771	–
2	Lstm_1 LSTM with 771 hidden units	LSTM	771	InputWeights, 3084×771 RecurrentWeights, 3084×771 Bias, 3084×1
3	Lstm_2 LSTM with 1542 hidden units	LSTM	1542	InputWeights, 6184×771 RecurrentWeights, 6184×1542 Bias, 6184×1
4	Dropout 50% dropout	Dropout	1542	–
5	Fc 3 fully connected layer	Fully connected	3	Weights, 3×1542 Bias, 3×1
6	Softmax_Layer Softmax	Softmax	3	–
7	Classification Layer crossentropyex	Classification output	–	–

Table 2. Confusion parameters.

Accuracy (A)	A is calculated as the number of all correct predictions divided by the total number of the dataset. The best accuracy is 1.0, whereas the worst is 0.0. It can also be calculated by 1 – ERR.	$A = \frac{TP+TN}{TP+TN+FP+FN}$
Sensitivity (S)	S is calculated as the number of correct positive predictions divided by the total number of positives. It is also called recall (REC) or true positive rate (TPR). The best sensitivity is 1.0, whereas the worst is 0.0.	$S = \frac{TP}{TP+FN}$
Precision (P)	P is calculated as the number of correct positive predictions divided by the total number of positive predictions. It is also called positive predictive value (PPV). The best precision is 1.0, whereas the worst is 0.0.	$P = \frac{TP}{TP+FP}$
F_1-Score (F_1)	F_1-score is a harmonic mean of precision and recall.	$F_1 = \frac{2TP}{2TP+FN+FP}$

TP: True Positive, TN: True Negative, FN: False Negative, FP: False Positive

Table 3. LSTM classification parameter.

Class	Accuracy	Precision	Recall	F1-Score
ARR	91.11%	0.836	0.891	0.86
CHF	93.19%	0.911	0.887	0.90
NSR	97.04%	0.973	0.94	0.96

vector in the last pooling layer of the Alexnet architecture, and its size is $6 \times 6 \times 256$.

In order to apply the architecture given in Figure 7 to ECG signals, the following two-step process has been applied.

First, the conversion of ECG signals to spectrogram images is performed. The spectrogram is a visual way to represent the signal strength or "height" of a signal at various frequencies. The procedure for calculating STFTs is to divide a longer time signal into shorter segments of equal length and then calculate the Fourier transform separately in each short segment. Then, the changing spectra are plotted as a function of time, known as the spectrogram chart. Equation (3) is used to calculate the STFT of a signal.

$$STFT\{x(t)\}(\tau, \omega) \equiv \int_{-\infty}^{\infty} x(t)\omega(t-\tau)e^{-i\omega t}dt \qquad (3)$$

Here, the *x[n]* signal is the *ω[n]* window. In this case, τ is time index and *ω* is continuous, in most typical applications STFT is performed on a computer using the Fast Fourier Transform, so both variables are discrete and quantitated. ECG signals are divided into eight segments with 50% overlap, and each segment is windowed with a Hamming window. Sample rate is 1 Hz.

Secondly, the spectrogram images are applied to crop and resizing.

The spectrogram images obtained at this stage are converted to the format that can be processed by Alexnet, namely $227 \times 227 \times 3$ size Figure 7. Arrhythmia shows the spectrogram image of an ECG signal belonging to the CHF and NSR classes.

The spectrogram images at the end of the above mentioned steps are classified with Alexnet-SVM. Test and training data have been chosen randomly. The feature vector in the pooling layer has been converted into a one-dimensional feature vector. This vector consisting of 9216 ($6 \times 6 \times 256$) features, has been given as an input to the SVM. Figure 8(a) shows the confusion matrix Figure 8(b) shows the change in accuracy.

The classification success achieved in accordance with Figure 8(a) is given in Table 4. According to Table 4, when each class is evaluated within itself, accuracy is 96.77%, 96.77% and 100% respectively. As a result, overall accuracy is 96.77. This result is an acceptable rate for detecting heart diseases.

5. Discussion

Arrhythmia (ARR) and congestive heart failure (CHF) are life-threatening heart diseases. Often arrhythmia leads to CHF. Therefore, it is very important for

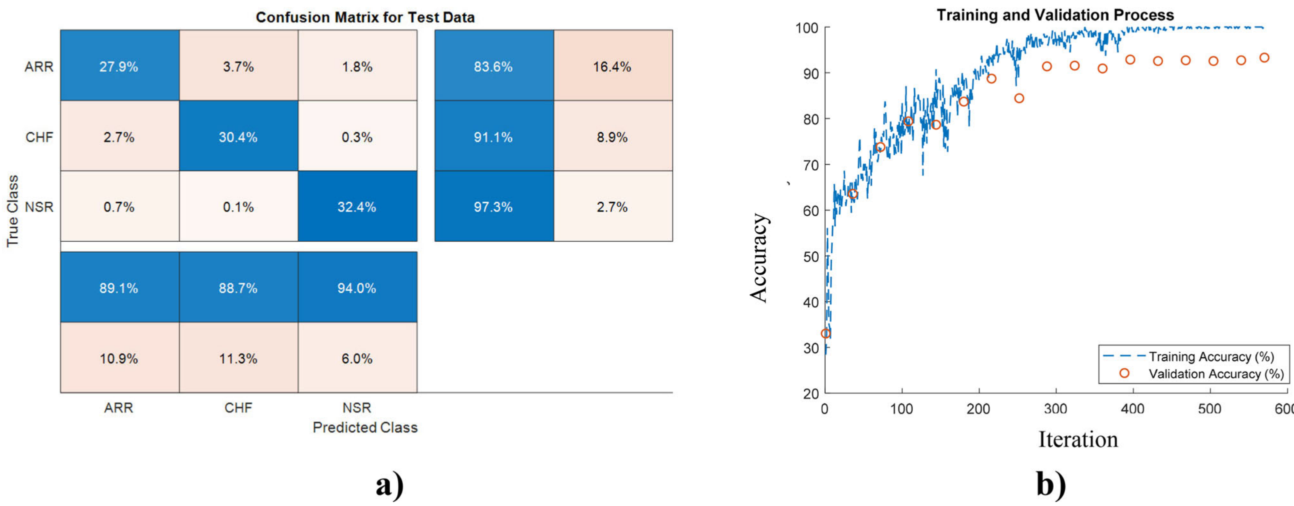

Figure 5. a) LSTM Confusion matrix, b) LSTM accuracy change.

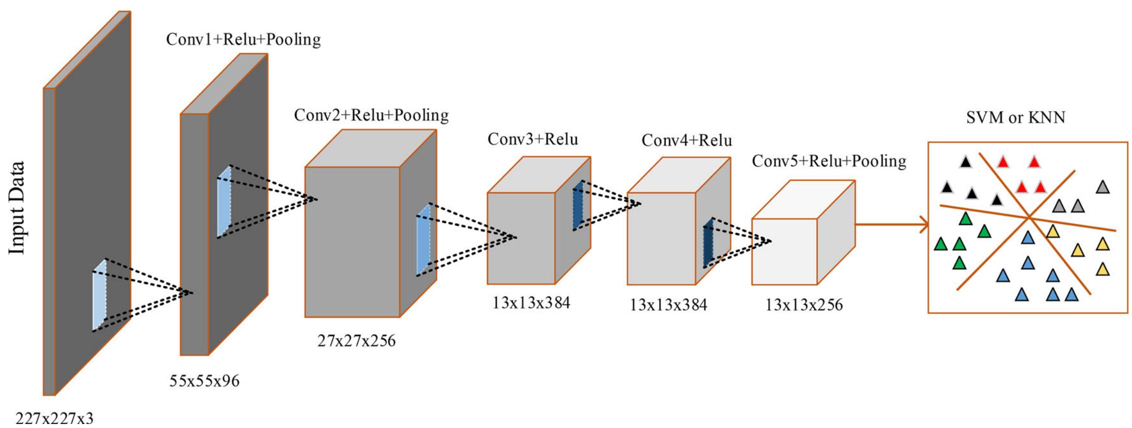

Figure 6. Hybrid Alexnet-SVM architecture.

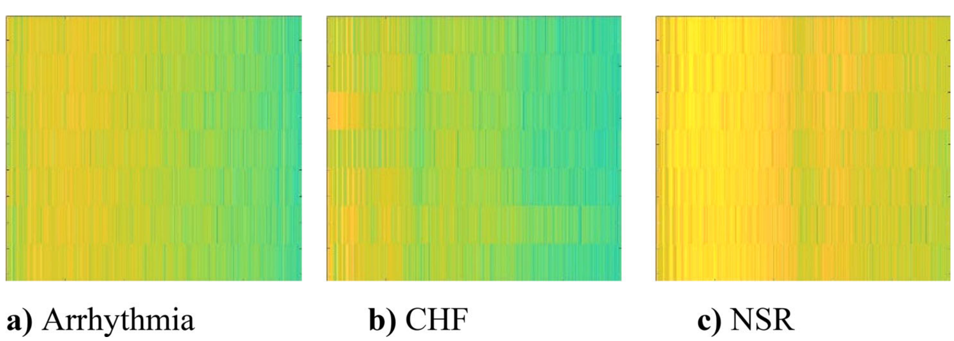

Figure 7. Example Arrhythmia, CHF and NSR spectrogram images.

doctors to distinguish between ARR, CHF and NSR. In this article, ECG Arrhythmia, CHF and NSR signals of 3 different classes are classified with the Alexnet-SVM method. First of all, raw ECG signals were converted into spectrogram images. Crop and resize operations were applied to the obtained spectrogram images. Thus, the images of $227 \times 227 \times 3$ size obtained have been processed by the Alexnet-SVM method. According to the results obtained, the proposed method has classified the ECG signals belonging to Arrhythmia, CHF and NSR classes better than existing algorithms from MIT-BIH database. Table 5 shows the comparison of the results obtained with the literature.

In the literature, Arrhythmia, CHF, NSR disorders are classified using both classical machine learning

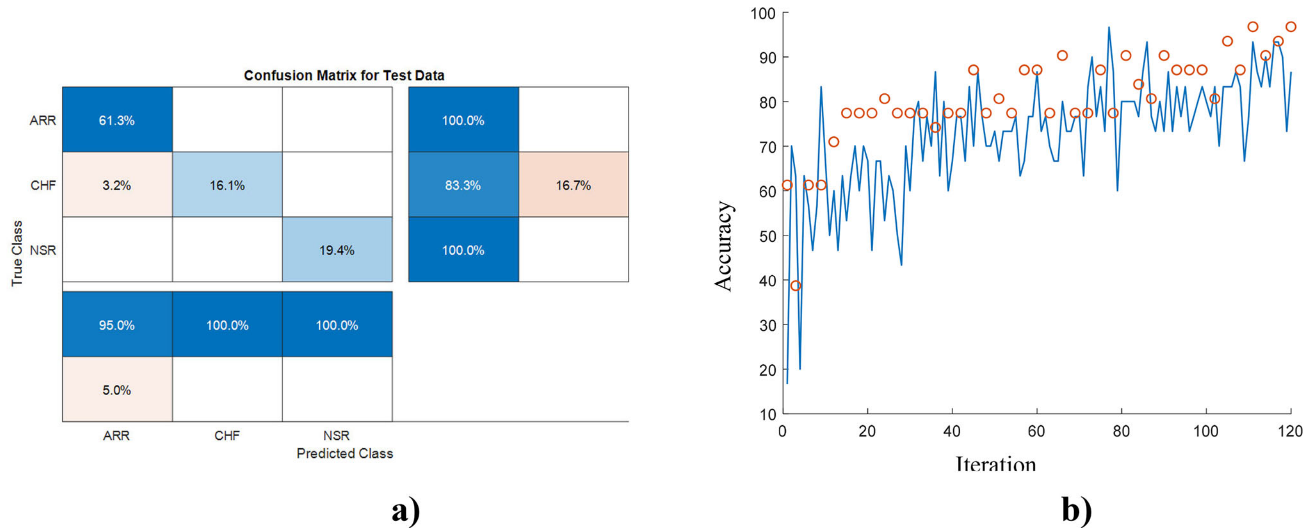

Figure 8. **a)** Alexnet-SVM Confusion matrix **b)** Alexnet-SVM Accuracy change.

Table 4. Alexnet-SVM classification parameters.

Class	Accuracy	Precision	Recall	F1-Score
ARR	96.77%	1.0	0.95	0.97
CHF	96.77%	0.83	1.0	0.91
NSR	100%	1.0	1.0	1.0

Table 5. Literature comparison.

Reference	Method	Performance	Class
Singh and Pradeep (2018)	Feature Selection, SVM, Random Forest, JRip	A = 85.58%	Arrhythmia
Isin and Ozdalili (2017)	Deep Learning	A = 92%	Arrhythmia
Vishwa et al. (2011)	Neural Network	A = 96.77%	Arrhythmia
Salem et al. (2018)	Deep Learning	A = 97.23%	Arrhythmia
Pomprapa et al. (2019)	Deep Learning	A = 99.2%	Arrhythmia
Zheng et al. (2020)	CNN,LSTM	A = 99.01%	Arrhythmia
Kim et al. (2009)	ELM	A = 98.72%	Arrhythmia
Son et al. (2012)	Rough Set, Logistic Regression	ROC = 97.5%	CHF
Chen et al. (2020)	CNN-LSTM	A = 99.32% A = 97.15%	sinus rhythm, ventricular bigeminy, pacing rhythm, atrial flutter sinus bradycardia.
Oh et al. (2018)	CNN-LSTM	A = 98.10%	sinus rhythm, left and right bundle branch block, Atrial premature beat, early ventricular contraction
Swapna et al. (2018)	CNN-LSTM	A = 83.4%	Arrhythmia
Sangaiah et al. (2020)	Hidden Markov Model	A= 99.8%	normal, LBBB, RBBB, PVC, APC Arrhythmia
Sharma et al. (2020)	LSTM	A = 90.7%	Arrhythmia
Isler (2016)	Multilayer Perceptron	A = 96.43%	CHF
Hussain et al. (2020)	SNN, KNN, Decision Tree	AUC = 0.97	CHF
Daqrouq and Dobaie (2016)	Wavelet Packet Transform, Feature Extraction	A = 92.6%	CHF,NSR
Nahak and Saha (2020)	Feature Fusion, SVM	A = 93.33%	ARR,CHF,NSR
Sandeep et al. (2019)	CNN	A = 90.63%	ARR,CHF,NSR
Faraggi and Sayadi (2019)	2D Neural Network	A = 97.6% A = 96.5% A = 92.6	ARR CHF NSR
Proposed Method	**Alexnet-SVM**	**A = 96.77%** **A = 96.77%** **A = 100%** **A = 96.77%**	**ARR** **CHF** **NSR** **All**

algorithms and new generation CNN architectures. In these studies, the MIT-BIH database was generally used and Arrhythmia ECG signals were classified with the highest 99.2% accuracy and CHF ECG signals with 97% accuracy. However, unlike the literature, Arrhythmia, CHF, NSR ECG signals are evaluated together in this article. Accuracy is not sufficient alone in unbalanced data, since it is calculated by the ratio of accurately estimated data to the total data set. Sensitivity measures how often a test works correctly, while specificity measures the ability of a test to produce negative results for the disease that is not being tested. Therefore, these parameters should be evaluated together. The F1-score, on the other hand, uses the harmonic average instead of the arithmetic mean to avoid ignoring extreme situations, so the F1-score must also be included in the evaluation metrics. Classification accuracy within each class is 96.77%, 96.77% and 100%. Overall accuracy was achieved with 96.77%. In addition, precision, Recall and F1-Score values were also high in parallel with the accuracy value. For F1-Score Arrhythmia, CHF, NSR classes, 97%, 91% and 100% were obtained, respectively. In order to show the accuracy of the results obtained in this article, it was shown that higher results were obtained by comparing the results obtained with Alexnet-SVM with the literature (Tables 3 and 4).

6. Conclusion

Due to the low amplitude, complexity and non-linearity of the ECG signal, it is difficult to manually perform in fast and accurate classification. For this reason, an automated system should be developed for use in the field of health, which can identify abnormal heartbeats different from large amounts of ECG data. In this article, LSTM and Hybrid Alexnet-SVM, one of the deep learning architectures, were used for the classification of Arrhythmia, Normal Sinus and CHF type waves in ECG signals. Confusion matrix and accuracy values were given to evaluate the results obtained. Compared with the most advanced methods, the proposed method has successfully classified Arrhythmia, Normal Sinus and CHF ECG signals. Consequently, the proposed method can be used as an auxiliary tool in clinicians' diagnosis of arrhythmia and CHF. As a future work, the number of data used and the number of diseases will be increased. Futhermore the effect of this situation will be examined on the proposed hybrid CNN architecture.

Disclosure statement

No potential conflict of interest was reported by the author(s).

References

Alarsan FI, Younes M. 2019. Analysis and classification of heart diseases using heartbeat features and machine learning algorithms. J Big Data. 6(1):1–15.

Association for the Advancement of Medical Instrumentation (AAMI). 2012. Testing and reporting performance results of cardiac rhythm and st segment measurement algorithms; ANSI/AAMI EC57. Arlington, VA, USA: Association for the Advancement of Medical Instrumentation.

Baim DS, Colucci WS, Monrad ES, Smith HS, Wright RF, Lanoue A, Gauthier DF, Ransil BJ, Grossman W, Braunwald E. 1986. Survival of patients with severe congestive heart failure treated with oral milrinone. J Am Coll Cardiol. 7(3):661–670.

Bulbul HI, Usta N, Yildiz M. 2017. Classification of ECG arrhythmia with machine learning techniques. 2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA); Cancun. p. 546–549.

Chen C, Hua Z, Zhang R, Liu G, Wen W. 2020. Automated arrhythmia classification based on a combination network of CNN and LSTM. Biomed Signal Process Control. 57:101819.

Daqrouq K, Dobaie A. 2016. Wavelet based method for congestive heart failure recognition by three confirmation functions. Comput Math Methods Med. 2016:7359516.

Faraggi M, Sayadi K. 2019. Time series features extraction using Fourier and Wavelet transforms on ECG data.

Hussain L, Awan IA, Aziz W, Saeed S, Ali A, Zeeshan F, Kwak KS. 2020. Detecting congestive heart failure by extracting multimodal features and employing machine learning techniques. Biomed Res Int. 2020:4281243.

Isin A, Ozdalili S. 2017. Cardiac arrhythmia detection using deep learning. Procedia Comput Sci. 120:268–275.

Isler Y. 2016. Discrimination of systolic and diastolic dysfunctions using multi-layer perceptron in heart rate variability analysis. Comput Biol Med. 76:113–119.

Kim J, Shin HS, Shin K, Lee M. 2009. Robust algorithm for arrhythmia classification in ECG using extreme learning machine. Biomed Eng Online. 8(31):31–12.

Masetic Z, Subasi A. 2016. Congestive heart failure detection using random forest classifier. Comput Methods Programs Biomed. 130:54–64.

MIT-BIH. 2020. Arrhythmia database. [accessed 2020 July 13]. https://physionet.org/content/mitdb/1.0.0/Access time.

Mustaqeem A, Anwar SM, Majid M. 2018. Multiclass classification of cardiac arrhythmia using ımproved feature selection and svm ınvariants. Comput Math Methods Med. 2018:1–10.

Nahak S, Saha G. 2020. A fusion based classification of normal, arrhythmia and congestive heart failure in ECG. 2020 National Conference on Communications (NCC). 2020.

Oh SL, Eddie YKN, Tan RS, Acharya R. 2018. Automated diagnosis of arrhythmia using combination of CNN and LSTM techniques with variable length heart beats. Comput Biol Med. 102:278–287.

Park J, Lee K, Kang K. 2013. Arrhythmia detection from heartbeat using k-nearest neighbor classifier. 2013 IEEE

International Conference on Bioinformatics and Biomedicine.

Pomprapa A, Ahmed W, Stollenwerk A, Kowalewski S, Leonhardt S. 2019. Deep learning of arrhythmia analysis based on convolutional neural network. Int J Bioelectromagnetism. 21(1):48–58.

Rajput KS, Wibowo S, Hao C, Majmudar M. 2019. On arrhythmia detection by deep learning and multidimensional representation. arXiv:1904.00138.7.

Salem M, Taheri S, Yuan J-S. 2018. ECG arrhythmia classification using transfer learning from 2- dimensional deep CNN features. IEEE Biomedical Circuits and Systems Conference. p. 1–4.

Sandeep K, Kora P, Swaraja K, Meenakshi K, Pampana LK. 2019. ECG classification using machine learning. Int J Recent Technol Eng (IJRTE). 8(4):2492–2494.

Sangaiah AK, Arumugam M, Bian G-B. 2020. An intelligent learning approach for improving ECG signal classification and arrhythmia analysis. Artif Intell Med. 103: 101788.

Sharma A, Garg N, Patidar S, Tan RS, Acharya R. 2020. Automated pre-screening of arrhythmia using hybrid combination of Fourier–Bessel expansion and LSTM. Comput Biol Med. 120:103753.

Singh N, Pradeep S. 2018. Cardiac arrhythmia classification using machine learning techniques. ICoEVCI 2018; India, p. 469–480.

Son CS, Kim YN, Kim HS, Park HS, Kim MS. 2012. Decision-making model for early diagnosis of congestive heart failure using rough set and decision tree approaches. J Biomed Informat. 45(5):999–1008.

Swapna G, Soman KP, Vinayakumar R. 2018. Automated detection of cardiac arrhythmia using deep learning techniques. Procedia Comput Sci. 132:1192–1201.

Toraman S, Tuncer SA, Balgetir F. 2019. Is it possible to detect cerebral dominance via EEG signals by using deep learning? Med Hypotheses. 131:109315.

Vishwa A, Lal MK, Dixit S, Vardwaj P. 2011. Clasification of arrhythmic ECG data using machine learning techniques. IJIMAI. 1(4):67–70.

Wang H, Shi H, Lin K, Qin C, Zhao L, Huang Y, Liu C. 2020. A high-precision arrhythmia classification method based on dual fully connected neural network. Biomed Signal Process Control. 58:101874.

Zheng Z, Chen Z, Hu F, Zhu J, Tang Q, Liang Y. 2020. An automatic diagnosis of arrhythmias using a combination of CNN and LSTM technology. Electronics. 9(1):1–15.