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Contemplate on ECG signals and classification of arrhythmia signals using CNN-LSTM deep learning model

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ABSTRACT

An electrocardiogram (ECG) is a schematic illustration of heart signals that is being used to measure the electric signals of the heart and to detect any abnormalities. Due to non-invasive qualities, the Electrocardiogram (ECG) has become a commonly employed auxiliary diagnostic index for heart problems in pre-screening and give information of heart diseases. Many methods are used to find out the abnormalities in heartbeat. In this paper survey is done to find out what are the methods used to classify the ECG recordings to predict cardiovascular diseases which affects middle aged as well as older people causing severe illness leading to death. One of the major abnormality was due to arrhythmia disease. Hence many deep learning methods were used to find early prediction of arrhythmia to save lives of people. From the survey it is found that many ECG classifications done using existing database such as MIT-BIH arrhythmia. Most of the methods work on classifications, feature extractions to find abnormalities in ECG signals and found to have higher accuracies of more than 94%.In this paper, the study is based on abnormalities in ECG signals due to arrhythmia and its identification using a network architecture based on LSTM and CNN deep learning methods. The simulation result shows the CNN- LSTM algorithm has higher accuracy compared to CNN.

1. Introduction

The electrocardiogram (ECG) is a standard for detecting and diagnosing irregular cardiac rhythms and is one of the most effective techniques used in hospitals to examine cardiovascular status and monitor health. Cardiovascular health has gotten a lot of attention in recent years. Traditional medical visits, on the other hand, have drawbacks such as delayed diagnosis and a high rate of misdiagnosis, whereas cardiovascular disorders offer the advantages of early diagnosis, early treatment, and early recovery. Cardiovascular disease is the main cause of death worldwide, and its mortality rate is rising [1]. One of the most common cardiovascular illnesses is atrial fibrillation, or AF. The electrical activity of the heart is reflected in ECG readings. As a result, abnormal cardiac rhythms or changes in the ECG waveform are indicators of underlying cardiovascular issues, such as arrhythmias. The identification and classification of ECG signals are essential to cardiovascular diseases. It is critical to diagnose arrhythmias early in order to give appropriate treatment. Long-term monitoring of the electrical activity of the heart (greater than 24 h) is required for early diagnosis of certain forms of transitory, short-term, or uncommon arrhythmia [2]. Devices, data collecting, and computer-aided diagnosis procedures have all improved thanks to the digital industry's rapid growth.

Nowadays, a computerized automated report can diagnose various cardiac problems and generate an automated report with a high level of accuracy [3]. Deep neural networks (DNNs) have recently demonstrated remarkable performance in tasks like image classification and speech recognition, and there are high hopes for how this technology can improve health care and clinical practice. DNNs might match [4] state-of-the-art methods for single-lead ECGs and, with a large enough training dataset, outperform practicing cardiologists.

The general ECG signal is given by Fig. 1. It is found that P Wave is the atrial depolarization wave, QRS Complex is the ventricular depolarization wave and T wave is the ventricular repolarization wave.

From the ECG signals the time period for contraction and relaxation was found as, P wave duration for atrial contraction, QRS wave ventricular contraction period, and T wave relaxation period of the ventricles which is shown in Fig. 2.

In this paper, the main factor considered under discussion is arrhythmia. The variations from the normal rhythm of ECG waves [5] and the sequence of excitation of the heart is known as arrhythmia.

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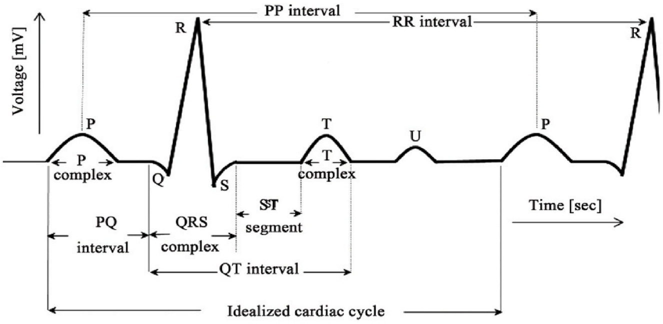

Fig. 1. Normal ECG Signal representation.

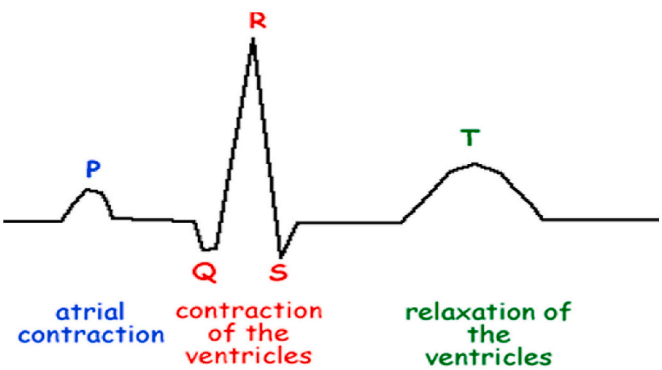

Fig. 2. Contraction and relaxation period of ECG signals.

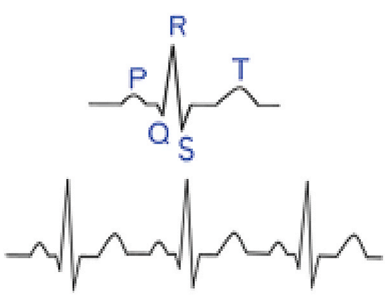

Fig. 3. Normal ECG signal.

Fig. 3 and Fig. 4 shows the difference between normal rhythm and arrhythmia abnormal signals.

All arrhythmia results from disturbances in the impulse formation and disturbance in the impulse conduction and during both formation and conduction [6]. The major four types of arrhythmia are Ventricular tachycardia, premature ventricular beats, Ventricular fibrillation, Torsades de pointes. Ventricular fibrillation, which is an uncontrolled, irregular heartbeat, is the most dangerous arrhythmia [7]. In this many impulses that all start at the same moment and tell the heart to beat which causes serious impact on the person suffering [8] because of this unbalanced impulse signals. The 12 lead electrodes were placed in order to identify the ECG signals whether it is normal or Abnormal which is shown in Fig. 5.

Fig. 4. Different abnormal ECG Signal.

The electrodes which are placed at the chest are explained as follows. (i) V1 is the Fourth intercostal space at the right border of the sternum, (ii) V2 is the Fourth intercostal space at the left border of the sternum, (iii) V3 is the Midway between placement of V2 and V4, (iv) V4 is the Fifth intercostal space at the midclavicular line,(v) V5 is the Anterior axillary line on the same horizontal level as V4, (vi) V6 is the Mid-axillary line on the same horizontal level as V4 and V5. The limb electrode placement is shown in Fig. 6.

2. Related work

Bhekumuzi [9] et al., proposed an operative method for ECG algorithm to classify arrhythmia using recurrence plot which can be used in portable devices. Variety of datasets was taken into account from physio Net to make a study. The proposed method made use of CNN classifiers which took input from segmentation of time series ECG signals converted using recurrence plot. The accuracy was improved by providing two stage classification. Several stages was used for this arrhythmia classification. Detection of ventricular fibrillation using ResNet-18 was done in the first stage. Premature ventricular contractions was carried out in the second stage. High accuracy output based on fivefold cross validation was obtained as 97 % along with sensitivity near to 96 % and 97%. The prediction values of 95 % and 98 % obtained. The F1 Score was about 95 % and 98% approximately. The memory requirement was improved. As much more data was used, it creates unbalanced in the first stage for classification.

Mohamed Sraitih [10] et al., aimed to project and explore classification done as automatic based on ECG data to provide arrhythmia detection without any feature extraction using machine learning methods. The supervised machine learning methods was explored. The ECG database having parameters such as NOR, PVC, PAC, RBBB were classified using some of the machine learning methods which were explored. The measurement was based on recall, f1-score, accuracy, precision. It was found that Support Vector machine method outbreaks other methods which was used for comparison producing accuracy of 0.83. The ECG signals are collected from many persons.

Wusat Ullah [11] et al., proposed a method using deep learning techniques to classify arrhythmia using classification on two different

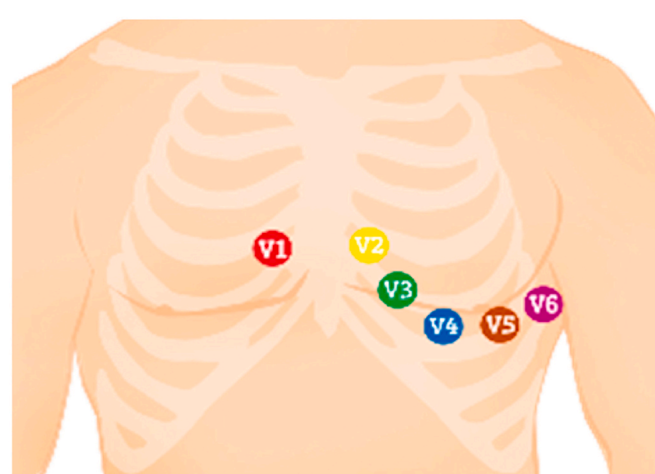

Fig. 5. 12-Lead ECG chest electrode placement.

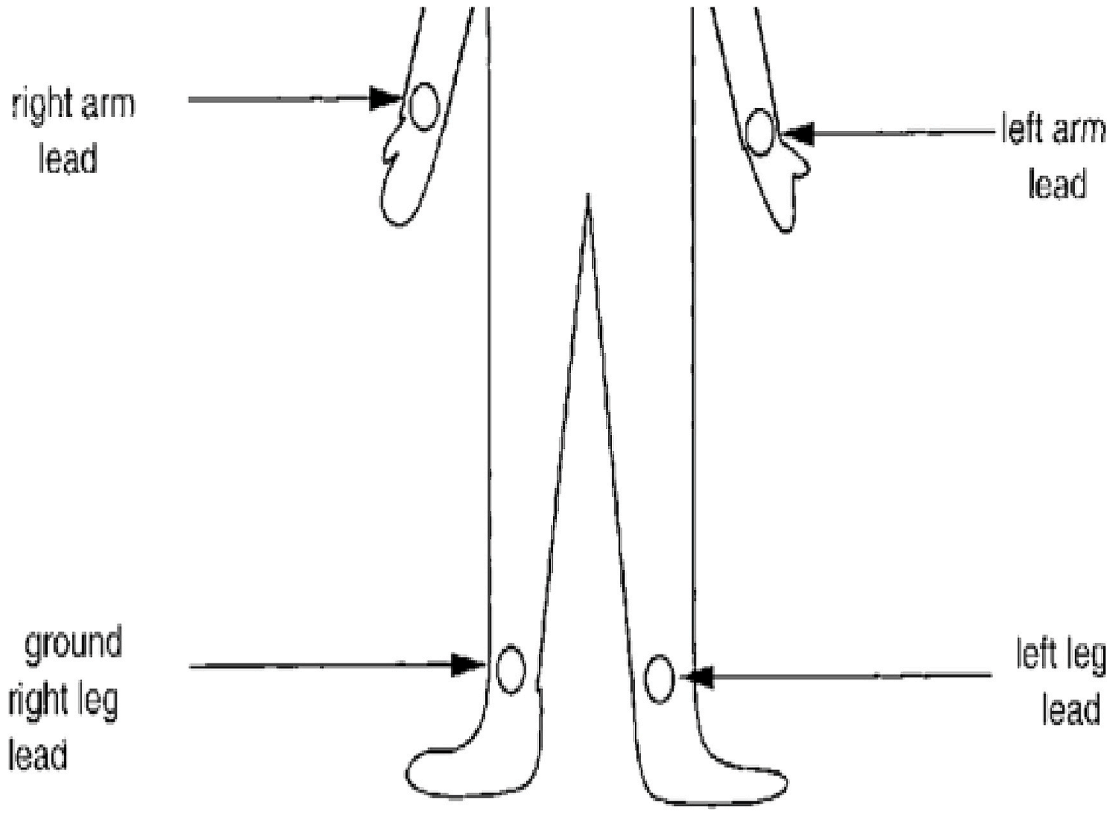

Fig. 6. Limb electrode placement.

database. One database from MIT-BIH arrhythmia ECG. The parameters included in the former dataset was V, F, S, N and Q. The second database consists of ECG PTB Diagnostic recordings. The models used by the later dataset were CNN alone, CNN with LSTM and CNN with LSTM and Attention Model. As deep learning methods used, training and testing was done having 80% and 20%. The results produced had accuracy of greater than 99 % for CNN alone, for combination of CNN, LSTM and Attention model, for combination of CNN with LSTM.

Saira Aziz [12] et al., developed a new algorithm based on ECG signals. The methods such as two event related moving averages along with fractional Fourier transform to classify ECG signals was proposed. The former algorithm provides desired ECG signal Peak specification, the later uses plane of time frequency to apparent various peaks of ECG signals. The state of art of the proposed algorithm was obtained. The features used was estimated peaks, different peak durations, heart disease which was automatically classified. More than 10,000 patients database was used for training the algorithm which was the basic for machine learning technique. The training and testing performed provides individuality to the proposed work.

Mengze Wu [13] et al., proposed a method based on CNN to classify heartbeat based on arrhythmia using dataset MIT-BIH. The feature classification made use of five types of parameters and threshold denoising method of wavelet transform was utilized. The comparison was based on different machine learning methods to show the results based on sensitivity, anti-noise capability. The accuracy shows that it can be used for clinical checking.

Fajr Ibrahem [14] et al., Proposed classification based on ECG signals having more features using machine learning methods. The Classification used Scala language and Machine Learning library in the framework of Apache Spark. The irregularities of ECG signals was detected in this proposed method. The impulse waveforms of ECG signals produced was classified using the machine learning methods. The features are described as the heartbeats will vary from person to person. The online database taken was from MIT-BIH Arrhythmia having 205,146 records to find the classification process. Many methods such as Gradient Boosted Trees (GBT), Decision Trees (DT) and Random Forest (RF) methods was analysed. The results showed that the accuracy was 97.98% in DT, then for 96.75% for GBT, 98.03% for Random Forest.

Wang, H [15] et al., Presented Convolutional Neural Network (CNN) model for high accuracy classification of arrhythmia signals. The improved CNN was modelled to classify irregularity in heartbeats based on online database. Kernels of various sizes were used in each convolutional layers along with max pooling layer. The fully connected layers gets its input from output of last pooling. The MIT Arrhythmia database was used for experiments comparison. The results showed that the output produced was having the accuracy of 99.06%.Because of the improved CNN model accuracy it can be used to detect different types of arrhythmia of ECG signals.

Aixia Guo [16] et al., used numerical embedding vectors to represent each patient's associated data collection time points and all time-series cardiovascular health (CVH) measures. Using a 5-fold cross-validation method, a deep learning technique called the long-short term memory (LSTM) model to predict CD from a vector of time-series CVH measures is employed. Then comparison of the performance model to that of deep neural networks, logistic regression, random forest, and Naive Bayes models is done. The results showed that the average area under the receiver operator curve (AUROC): 0.76 for LSTM, 0.71 for deep neural networks, 0.66 for logistic regression, 0.67 for random forest, and 0.59 for Naïve Bayes. The most influential feature from the LSTM model were blood pressure.

Ilaria Gandin [17] et al., implemented Long Short-Term Memory (LSTM) neural network of an attention layer to provide a helpful insight on the influence of the numerous input variables incorporated in the model. In terms of AUC, the LSTM model performs at a level of 0.790. The impact of attention weights in relation to the model interpretability. The results showed excellent correlation with transparent model driving predictors (r = 0.611, 95% CI [0.395, 0.763]).

3. Proposed hybrid CNN-LSTM model

(i) Convolutional Neural Network (CNN) Method

The fundamental principle of a CNN is that it can extract local features from inputs at high layers and transfer them to lower layers for more complex features. Fully connected (FC), convolutional, and pooling layers make up a CNN. The operation of the convolutional layer is given by the equation:

$$F(i, j) = (I * K)(i, j) = \sum\sum I(i + m, j + n)K(m, n) \quad (1)$$

where I refers to the input matrix, K denotes a 2D filter of size $m \times n$, and F represents the output of a 2D feature map. The operation of the convolutional layer is denoted by I*K. Rectified linear unit (ReLU) layer is utilized in feature maps to boost nonlinearity. The mathematical formula is given by,

$$f(x) = \max(0, x) \quad (2)$$

To minimise the number of parameters, the pooling layer down-samples a specific input dimension. The most common method, which yields the greatest value in an input region, is max pooling.

(ii) Long Short Term Memory (LSTM) Method

Recurrent neural networks (RNN)are strengthened by long short-term memory. LSTM is combined with three gates, such as an input gate, a "forget" gate, and an output gate. Where xt represents the current input, C_t and C_{t-1} indicate the new and prior cell states, respectively, and h_t and h_{t-1} which denote the current and past outputs, respectively.

The principle of the input gate of LSTM is shown in the following forms.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (3)$$

$$\tilde{C}_t = \tanh(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (4)$$

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t \quad (5)$$

where (8) is used to pass h_{t-1} and x_t through a sigmoid layer to decide on which portion of information should be added. New information after h_{t-1} and x_t are passed through the tanh layer. The current moment information, C˜t, and long-term memory information Ct− 1 into Ct are combined in (10), where Wi refers to a sigmoid output, and $\tilde{C}_t$ refers to a tanh output.

In this proposed method, CNN and CNN-LSTM is used to classify the ECG signals whether the person is normal or abnormal not. The steps involved are a) Getting of Raw data or real time data through sensors, b) Preprocessing of data obtained, c) Feature extraction and Feature selection, d) Classifier classification as normalECG or abnormal ECG, e) To calculate the performance factors. Fig. 7 gives the complete flow of the findings of normal and abnormal ECG signals (arrhythmia signals).

a) **Input Data:** The data can be real time data using wearables or online dataset for example MIT-BIH dataset as it gives proper information regarding cardiac problems. Database contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory. Twenty-three recordings were chosen at random from a set of 4000 24-h ambulatory ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample. sources: https://physionet.org/content/mitdb/1.0.0/. The ECG recordings were sampled to a frequency range of 360Hz.

b) **Preprocessing of data:** The signals what we provide will have noise. So it is necessary to remove noise which is done at preprocessing stage. The noises can be of different types such as frequency noise, impulsive noise, even muscle noise [18]. To remove all the noises many methods are implemented to extract original signals from noise. Some of the methods are Finite Impulse Response, Gaussian filters, wavelet coefficient threshold, median filters etc., but we need to find out correct filtering algorithm to eliminate noise from the ECG signals. For signals, features can be frequencies varying over time, transients, or slowly varying trends which is processed by wavelet transform.

b) **Feature extraction and Feature selection:** This step plays an important role to split the signals according to the features involved in it. This process mainly depends on the original signals. The feature extraction seeks to reduce the amount of features in a dataset by generating new ones from old ones. The most common method used for feature extraction is wavelet transform method [19]. Some other methods are Denoising Auto encoder, Sparse Auto encoder, Convolutional Auto encoder, Variational Auto encoder. Feature selection is the process of decreasing the input variable to the model by only using necessary data and removing noise from the data. Features such as Structural and chronological were extracted from the input ECG signals. Feature selection will be based on different techniques such as Genetic Algorithm, wrapper methods, embedded methods.

c) **Noise Removal:**ECG denoising is done in order to remove noise from the signal to extract original ECG signals. Consider an N -sample observed data,

$$\psi\ (2)\ (t) = \psi h(t) + i\psi g\ (t) \quad (6)$$

Where $i = \sqrt{-1}$, ψh(t) is a real and even function, whereas ψg (t) is an imaginary and an odd function. These two functions are implemented so that ψg (t) is the Hilbert transform of ψh(t) in order to ensure the perfect reconstruction of the decomposed signal.

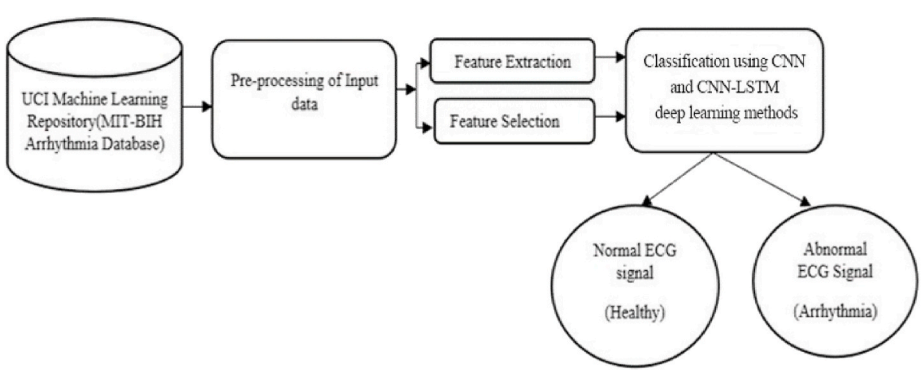

Fig. 7. Steps involved to identify Normal and Abnormal ECG signals.

d) **Classifier:** The classification process is done to improve the boundary conditions. Identification of the target class after the boundary conditions have been determined will be followed [20]. Some of the classifiers are Support vector Machine, Kernel estimation, Neural networks etc. In the suggested approach, balancing the database is the first step toward pre-processing. A database frequently has an uneven distribution of samples across its several classes. When the number of samples in a class differs significantly from the number of samples in other classes, the likelihood of error during classification rises. As a result, the method used to identify samples becomes sensitive to the class with the greatest number of examples in the database. Data balancing is therefore crucial in these uneven or imbalanced databases. Techniques for resampling samples into each class in a database are those that are used to balance the samples across each class. By classification it is necessary to find out the person is having health ECG or abnormal ECG. The classification is done based on training and testing shown in Fig. 8 with percentage of splitting.

In order to assess the neural network's performance, the network was first trained by providing it with data from the "training set," after which it was validated using the data from the "validation set" to find the percentage of loss and accuracy. To assess and verify the neural network's robustness to data outside of the training/validation set, the "testing set" was used in the end.

e) **Performance Factors:** The performance factors are used to classify the input (real time or online dataset) ECG signals normal or abnormal [18]. Some of the factors are Specificity, Sensitivity, True positive values, False positive Values, True negative Values, False negative Values which is shown in Table 1.

The formulae to calculate Sensitivity and Specificity is

$$\text{Accuracy} = (\text{TPV} + \text{TNV})/(\text{TNV} + \text{FPV} + \text{TPV} + \text{FNV}) \tag{7}$$

$$\text{Sensitivity} = \text{TPV}/(\text{TPV} + \text{FNV}) \tag{8}$$

$$\text{Specificity} = \text{TNV}/(\text{TNV} + \text{FPV}) \tag{9}$$

The AUC—area under the curve is determined by calculating

$$\text{TFP} = \text{true positive rate} = \text{TP}/(\text{TP} + \text{FN}) \tag{10}$$

$$\text{FPR} = \text{false positive rate} = \text{FP}/(\text{TN} + \text{FP}) \tag{11}$$

From the formula stated above we can find the accuracy of the algorithm used from which we can decide which model to be chosen for prediction of arrhythmia disease. Different methods which shows accuracy of the prediction is shown in Table 2.

From the above Table 2 it is found that the accuracy ranges from 86% to 99.06% for Hybrid Classifier,Ensemble Classifier and CNN. In this paper,a proposed method using CNN-LSTM model to increase the accuracy to 97% is done.

Table 1
Parameters use in Deep Learning methods.

S. No	Factors	Abbreviation	Finding
1	Sensitivity	SEV	Number of patients with disease
2	Specificity	SPV	Number of patients without the disease
3	True positive values	TPV	Positive test means patient is suffering from disease
4	False positive	FPV	Positive test means the patient is not suffering from disease
5	True negative	TNV	Negative test means the patient is not suffering from disease
6	False negative	FNV	Negative test but the patient has the disease.

Table 2
Different classification methods with accuracy.

Classifier Type	Usage	Accuracy obtained
Hybrid Classifier [1]	Feature Extraction: Genetic Algorithm Classification: Decision Tree	86.96%
Ensemble Classifier [14]	Feature Extraction: XGBoost Classification: Random Forest Voting Classifier was used	76%
Convolutional Neural Network (CNN) [11]	Walsh function to convert 1 D images to 2 D images.	99%
Improved CNN [15]	Improved CNN was trained as tool to find out arrhythmia disease	99.06%
Proposed CNN-LSTM method	Hybrid of CNN and LSTM to find arrhythmia disease	99.4%

4. Simulation results and discussions

In this paper training and testing is done using CNN and CNN-LSTM deep learning methods for the MIT-BIH arrhythmia dataset which is commonly used because of its originality in ECG signals data. The frequency of recordings is taken not less than 360Hz.Based on the input signals provided by the online dataset, the ECG signals are classified as normal and abnormal signals by loading a single patient's signals and annotations. The annotation values used are the indices of the signal array and it is plotted as graphical representation shown in Fig. 9.

The dataset for the experiment was divided into training and testing groups of 80% and 20%, respectively. Using the 5-fold cross-validation technique, the results were obtained. The suggested network has 12 convolutional layers, a learning rate of 0.0001, and a maximum number of epochs of 125, as measured experimentally. On an Intel(R) Core(TM) i7-2.2 GHz processor, the CNN and CNN-LSTM networks were constructed using Python and the Keras package with TensorFlow2. The dataset is centered on before and after beats with +- 3 s. Categorical cross entropy, Gradient descent algorithm with exponentially weighted average for classification is done. First the splitting is done based on samples of the patients from the database. Next the splitting is done based on individual patients not on samples. The parameters calculated are Area under the Curve (AUC), Accuracy, Recall, Precision, and Specificity. The values obtained are shown in Table 3 and Table 4 for CNN and Hybrid of CNN-LSTM.

The value of sensitivity (99.3%) means that the sum of the false negatives is low while the specificity value (99.2%) means that the sum of the true negatives is high from equation (2) and equation (3).

The classification is done using categorical cross entropy, and the Adam optimizer which is shown in Fig. 10 for AUC. It is found that more data appears to add extra value to the model.

Fig. 11 and Fig. 12 shows the graphical plot of CNN and CNN- LSTM model for training and validation. The training and validation accuracy is 96.8% and 96.2%, respectively, at epoch 125 for CNN. Similarly accuracy is 97.3% and 97.0%, respectively, at epoch 125 for CNN-LSTM model. When compared to CNN, it is discovered that the CNN-LSTM model offers good dataset validation.

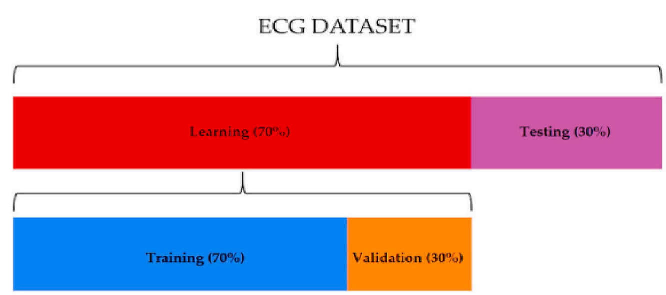

Fig. 8. ECG Segments distribution.

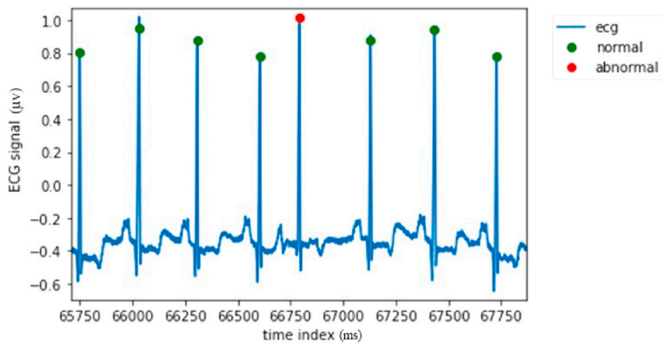

Fig. 9. Normal and abnormal ECG signals.

Table 3
Parameters -training and Validation(CNN).

Parameters (Samples)/(Patients)	Train	Validation
AUC	0.992/0.993	0.988/0.954
Accuracy	0.968/0.977	0.962/0.951
Recall	0.962/0.956	0.951/0.992
Precision	0.937/0.966	0.929/0.896
Specificity	0.972/0.986	0.967/0.951

Table 4
Parameters -training and Validation(CNN-LSTM).

Parameters (Samples)/(Patients)	Train	Validation
AUC	0.993/0.994	0.994/0.935
Accuracy	0.997/0.992	0.995/0.993
Recall	0.956/0.962	0.992/0.922
Precision	0.966/0.968	0.916/0.921
Specificity	0.986/0.987	0.963/0.972

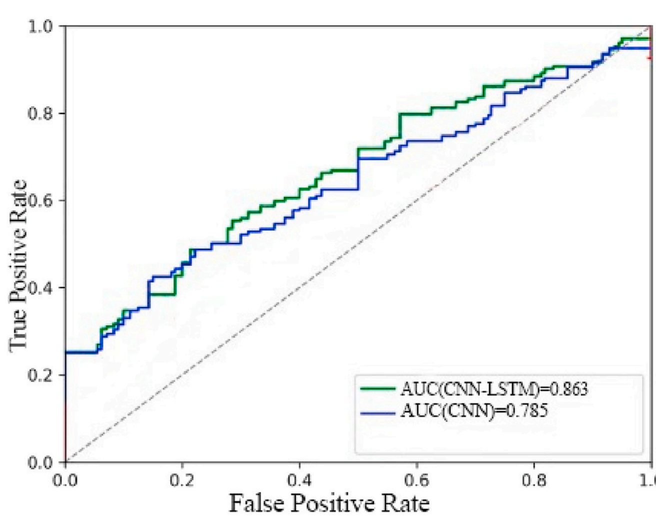

Fig. 10. Plotting of Area under the curve for CNN and CNN-LSTM.

Number of Epochs and Loss are represented on a graph in Fig. 13 and Fig. 14. For the CNN design, the training and validation losses are 0.09 and 0.26, respectively. The CNN-LSTM architecture has a training loss of 0.05 and a validation loss of 0.07, respectively. The CNN-LSTM architecture outperformed the CNN architecture in terms of training and validation accuracy scores.

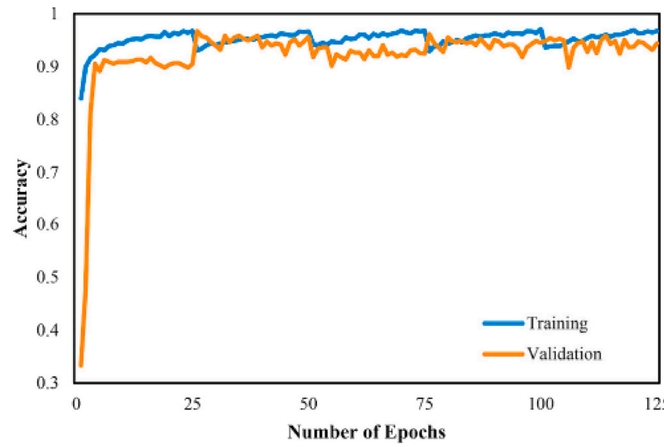

Fig. 11. CNN model -accuracy train and validation.

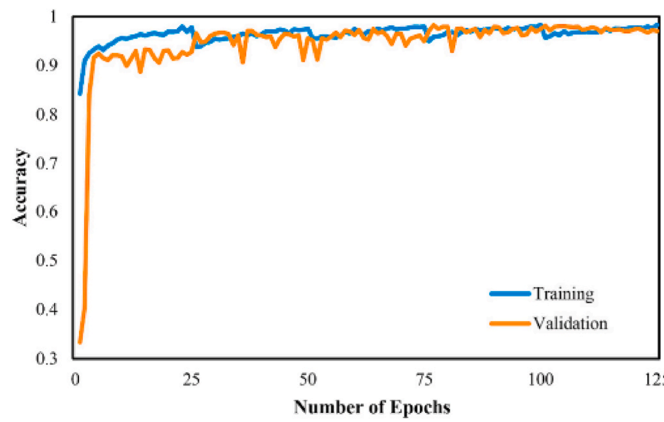

Fig. 12. CNN- LSTM -accuracy train and validation.

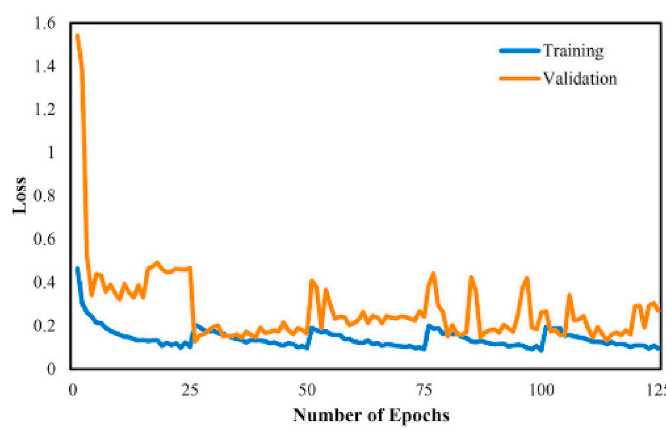

Fig. 13. CNN - loss train and validation.

5. Conclusion and future scope

In this proposed work CNN and CNN-LSTM ECG classification is done. The feature extraction along with feature selection methods were studied for finding of arrhythmia disease of a person. The accuracy of CNN-LSTM gets increased to 97 % when compared to CNN with 96%. The method based on hybrid deep Learning techniques CNN-LSTM produce good accuracy compatibility along with computational complexity when compared with CNN to classify ECG Signals. We hope that the proposed system would be able to develop a tool for ECG

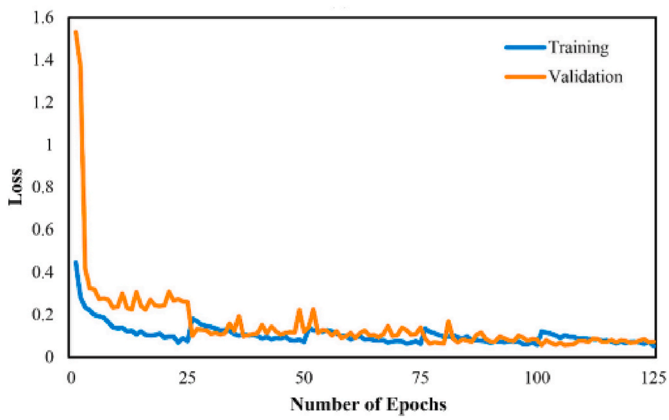

Fig. 14. CNN-LSTM -loss train and validation.

patients and reduce the workload of the medical diagnosis for ECG. It has some limitations. First, a larger sample size is required to test the generalizability of the created system because it is now quite little. Second, multiple disease symptoms cannot be efficiently classified.

In future hybrid CNN-LSTM algorithms will be used to detect anomalies in ECG signals early and connect to hospitals for doctors and emergency services like ambulances through edge computing. This will be especially helpful when there is a pandemic and individuals are unable to go to the hospital for regular checkups.

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Informed consent statement

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CRediT authorship contribution statement

S. Sowmya: Conceptualization, Validation, Resources, Writing – original draft, Visualization, All authors have read and agreed to the published version of the manuscript. **Deepa Jose:** Methodology, Formal analysis, Investigation, Writing – review & editing, Supervision, All authors have read and agreed to the published version of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data collected from public data base. (https://www.physionet.org/content/mitdb/1.0.0/))

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