RESEARCH PAPER

ECG Arrhythmia Classification using Deep LSTM Network with Hybrid Feature Extraction

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Abstract –
Electrocardiogram (ECG) signals are vital for detecting cardiac arrhythmias. Medical professionals typically do this diagnosis to detect certain malfunctioning of heart. In such a detection subjectivity arises and also the detection may not be accurate therefor it is important to develop automatic detection and classification techniques. In the past most of the researchers have classified up to 6 cardiac arrythmias and reported their classifier capabilities. It is difficult to accurately classify ECG when there are more arrhythmias to classify. A deep Long Short-Term Memory (LSTM) network is proposed in this paper which classifies 7 arrhythmia types using hybrid features extracted from temporal and frequency domains. The hybrid approach combines Discrete Wavelet Transform (DWT)-based features with statistical descriptors to enhance discriminative power. Training and validation were done on the proposed network using the MIT-BIH Arrhythmia Database (ADB), achieving overall average accuracy, precision, recall and F-score of 99.43%, 99.44%, 99.45% and 99.41% respectively, outperforming traditional CNN and standalone LSTM architectures. These results demonstrate that integrating hybrid features with deep LSTM networks significantly improves ECG classification performance, supporting automated clinical diagnosis. Proposed method's performance is compared with some of the standard existing methods and it was observed that the presented method outperformed numerous existing methods. The hardware requirement and processing time is also less as compared to other methods.

Keywords - ECG, Arrhythmia, LSTM, Deep Learning, Hybrid Features, DWT, MIT-BIH
How to cite this article: Mishra AK, Yadav KP, Dewangan NK. ECG Arrhythmia Classification using Deep LSTM Network with Hybrid Feature Extraction. Int J Drug Deliv Technol. 2026;16(11s): 254-268; DOI: 10.25258/ijddt.16.11s.24.

1. Introduction

A variety of diseases claim the lives of millions of individuals each year. Cardiac and diabetic patients are increasing day by day all over the world. As per the Global Health Report cardiac problems are the primary cause of death [1]. It is very common to analyze the patients ECG to diagnose the cardiac diseases. A patient's premature mortality can be avoided by early identification and medical treatment of numerous heart conditions. Rural part all over the world faces the problem of less or no physicians available, computer aided diagnostic system analyses the ECG signal without them and finds out various abnormalities present in the patient's heart. Humans' manual interpretation of ECG readings is very subjective and qualitative. Quantitative assessment of disease is possible by computer analysis. It provides handy tools to the physicians. The computer aided analysis will save time of patients because they are not required to wait for the availability of physicians.

Fig. 1 illustrates the stages in the classification of cardiac arrythmias.

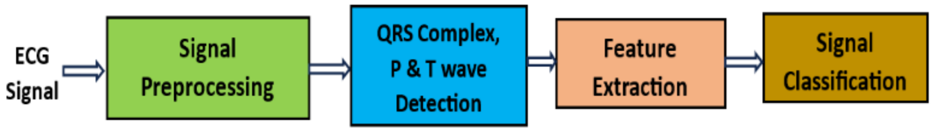


Fig. 1. Stages in the classification of cardiac arrhythmias.

Base line adjustment, normalization, and noise removal are all part of signal pre-processing. The subsequent stage is to identify the Q, R, S points, P and T wave. The third stage is to find and calculate suitable features for the signal classification. ECG signal classification can be performed using a variety of feature types, including features derived from morphology, statistics, frequency domain fast Fourier transform (FFT) analysis, and wavelet decomposition. Morphological features are derived from peak characteristics and temporal intervals present in the ECG waveform. Statistical features include parameters such as mean, median, mode, energy, and variance computed from the ECG signal. In wavelet-based analysis, the coefficients obtained after decomposing the ECG signal to an appropriate level are used as discriminative features, while FFT-based features are obtained from the Fourier coefficients of the transformed signal. These features exhibit noticeable variations under abnormal

*Author for Correspondence: anurag020981@gmail.com cardiac conditions, making them effective for ECG signal categorization. Along with morphological characteristics, statistical, wavelet, and FFT-based parameters are widely employed in ECG classification tasks. However, the effectiveness of a feature set is highly dependent on the classification technique used, and features that perform well for one classifier may not yield similar results for another. Owing to the complex and unknown interrelationships among features, identifying an optimal feature set for a specific classifier in advance remains a challenging task. The features selected are given to the classifier to categorize the signal into a particular class in which they belong, constitute final and fourth step. ECG classification has been addressed using a wide range of techniques, including Support Vector Machines (SVM), Self-Organizing Maps (SOM), Hidden Markov Models (HMM), Fuzzy Logic (FL), Neuro-Fuzzy Approaches (NFA), Principal Component Analysis (PCA), Genetic Algorithms (GA), Bayesian methods, Autoregressive (AR) models, and other statistical classifiers. Over the past few years, artificial intelligence–based approaches have attracted considerable research interest, particularly deep learning methods such as Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs), as well as hybrid learning models that fuse multiple paradigms.

In this paper a Deep LSTM network is designed to classify 7 cardiac arrhythmias which may be present in ECG recordings associated with abnormal cardiac activity. In the MIT-BIH ADB, which is made available by pysionet.org, 7 types of cardiac rhythms are considered for classification: left bundle branch block (L), right bundle branch block (R), paced beats (/), premature atrial contractions (A), premature ventricular contractions (V), ventricular escape beats (E), and normal beats (N). Using the MIT-BIH Arrhythmia Database (ADB), this paper proposes a novel deep Long Short-Term Memory (LSTM) network architecture to classify 7 different forms of cardiac arrhythmias. The dataset was formed and separated into training and testing data by partitioning. Newly developed deep learning LSTM model undergoes training and testing on balanced dataset using 10-fold cross validation to classify heartbeats into 7 classes. The proposed classifier is assessed using accuracy, precision, recall, and F-score as performance measures. A performance comparison of the proposed approach was conducted with some of the established techniques. Experimental evaluation demonstrates that the proposed model provides improved performance relative to previously reported approaches.

2. Work Done in the Past

This section briefly reviews some of the previous studies on the methods for extracting features and classifying ECG signals. All ECG classification system involves signal preprocessing, extraction of important features and finally classification tools to classify each ECG beats into different classes.

ECG signal might be buried by different noises when it is recorded, and various waves present in it might not be detected and because of this analysis may not be accurate. Preprocessing is performed to remove noises present in the ECG. The effectiveness of any ECG signal classification system is largely dependent on the accurate identification of the QRS complex along with the P and T waves as well, therefore signal denoising is required before analysis can begin.

In ECG signals noise arises from electrical power lines called power line interference (PLI) having frequency of 50 Hz, muscle noise of higher frequency and noise due to motion artefacts of relatively lower frequency as baseline drift (BLD) [2]. Discrete Wavelet Transform (DWT) based techniques were used by [3], [9], [14], [25] and [29] to remove noises manifested in the ECG waveform. Saini *et al.* [10] used a low-pass filter (LPF) with a 100 Hz cutoff to remove high-frequency noise and BLD was eliminated by subtracting an estimated low-order polynomial from the signal [10]. In order to maximize the QRS complex energy, Rangappa *et al.* [17] employed a band-pass filter designed to preserve signal components within the 4–15 Hz range. A band-pass filter (BPF) is created by cascading the LPF with a high-pass filter (HPF), which automatically eliminates undesired low- and high-frequency noise components [17]. Park *et al.* [13] employed a filter configured with a 0.1–100 Hz passband to suppress noise components in the recorded ECG.

Once ECG signals are denoised next step in the classification process is the detection of distinguished wave present in the ECG. P, T waves and QRS complexes can be easily distinguished in ECG signals. Therefore, it is essential to build a computer-aided tool for classifying heart diseases. Haibing et al. proposed a QRS detection technique using Dyadic wavelet transform DyWT [4]. DWT-based analysis was applied to accurately locate R-peaks, enabling reliable determination of the QRS complex in ECG signals by Banerjee *et al.* [5]. The study by Narayana *et al.* [6] analyzed the performance of wavelet transform and derivative-based Pan–Tompkin's methods in QRS wave detection from ECG data. Sasikala *et al.* [7] emphasized on identifying P and T waves by employing WT.

Reliable detection of the principal ECG components: P wave, QRS complex, and T wave is fundamental for the extraction of ECG morphological features. However, it has been observed that integrating morphological features with complementary feature sets leads to a substantial improvement in classification performance. Consequently, the identification of an optimal and discriminative feature set for enhancing classification accuracy remains an open challenge for future investigation.

The classifier utilizes extracted features as input, which encapsulate the underlying characteristics of the signals. The feature selection stage is designed to derive a minimal yet discriminative feature subset required to achieve satisfactory classification performance. Developers are generally unable to assess features' role in the classification process without training and testing the classifier. Accordingly, multiple training iterations are performed using different feature combinations to optimize classifier performance until an acceptable level of accuracy is achieved. Consequently, enhancing classification accuracy while incorporating additional classifiable cardiac arrhythmias should be a primary objective of ECG signal analysis. In their work, Sarkaleh *et al.* [9] utilized DWT-based feature extraction in conjunction with an ANN classifier to differentiate between two arrhythmia classes. Saini *et al.* [10] suggested an approach for the identification and categorization of 4 distinct arrhythmia types using a backpropagation neural network (BPNN) trained on standard ECG data. The classification process was based on three morphology-based features, namely R-peak value, RR interval, and QRS duration [10]. Martis *et al.* [12] investigated 5 distinct ECG beat classifications of arrhythmia in their research. Park *et al.* [13] developed a newly methodology for automatic categorization of ECG beat tailored for Holter monitoring applications. Dewangan *et al.* [14] used a 3-layer feedforward backpropagation neural network which is trained by hybrid features i.e. 4 morphological and 8 wavelet features to classify 6 types of arrhythmias. Bassiouni *et al.* [16] extracted morphological information from the dataset using DWT. The Teager energy operator and ICA's were used to improve the categorization of arrhythmias [16]. Rangappa *et al.* [17] distinguished 5 different classes of ECG beats based on a three-stage processing scheme. In the first stage, R- peak detection is performed using the Pan–Tompkin's algorithm. The second stage combines the extracted interval features with higher-order statistical intrinsic features of the ECG waveform. The third stage employs the k-Nearest Neighbor (k-NN) technique for the categorization of ECG [17]. Kiani *et al.* [18] used BPN and the fractal dimension for accurately diagnosing 7 arrhythmias. Dalal *et al.* [19] introduced a robust, fast and precise method for ECG-based cardiac health assessment. DWT is utilized for noise reduction in the ECG signal and by using several cumulants, characteristic features are obtained. For signal classification, the Kernel Extreme Learning Machine (KELM) is used, and multi-cumulant features and KELM parameters are optimised using Genetic Algorithms (GA) [19]. Halemirle *et al.* [20] proposed a categorization method based on hybrid features. Feature extraction was performed using autoregressive modeling, SVD entropy, dual-tree complex wavelet transforms, and multifractal analysis. The resulting features were then input to k-Nearest Neighbor (k-NN), Bayesian-optimized k-NN, and Random Forest classifiers for the classification task [20]. Sehirli *et al.* [21] introduced an intelligent framework for the classification of ECG datasets into 7 groups by using a hybrid model of machine learning. The Q, R, and S waves are extracted using k-means clustering in conjunction with local extrema detection [21]. Wu *et al.* [22] classified 5 distinct arrhythmias by proposing an efficient and high-accuracy 12-layer 1D convolutional neural network architecture (1D CNN). The designed model demonstrated higher accuracy and improved robustness compared to existing CNN models, Random Forests, and backpropagation neural networks (BPNN) [22]. Sahoo *et al.* [23] introduced a framework built upon deep learning techniques for the automatic classification of 5 distinct cardiac arrhythmia classes, employing hybrid feature representations and a ten-fold cross-validation strategy for performance evaluation. Bhatia *et al.* [24] presented an automated ECG heartbeat classification methodology which combines a deep CNN with BLSTM model to discriminate among 5 heartbeat classes. Rai *et al.* [25] introduced an ECG abnormality detection approach based on multi-scale WT analysis and an ANN classifier. Zabihi *et al.* [28] employed a hybrid framework combining machine learning– and deep learning–based methods for classifying ECG signals. Cui *et al.* [29] applied an interpretable Kolmogorov–Arnold Network (KAN) for ECG arrhythmia classification. Zhang *et al.* [30] performed inter-patient ECG heartbeat classification across three heartbeat categories using an adversarial convolutional neural network (CNN). El-Ghaish *et al.* [31] proposed an ECG based arrhythmia classification framework leveraging a bidirectional transformer-based architecture to discriminate among 5 distinct arrhythmia classes. Farag *et al.* [32] introduced a compact convolutional neural network (CNN) classifier for real-time ECG monitoring at the edge, leveraging matched filter (MF) theory for enhanced signal detection for inter-patient ECG classification and on-device arrhythmia detection, enabling robust discrimination among 5 arrhythmia classes under resource-constrained conditions. Kumar *et al.* [33] introduced Fuzz-ClustNet, a hybrid framework that combines fuzzy clustering with deep neural networks for ECG-based arrhythmia detection, enabling the classification of 6 distinct classes. Kachuee *et al.* [34] developed an ECG heartbeat classification framework using deep transfer learning to learn transferable feature representations, enabling robust discrimination among 5 distinct arrhythmia classes across varying patient data. Islam *et al.* [35] proposed CAT-Net, a hybrid deep learning architecture integrating convolutional, attention, and transformer modules for the classification of five single-lead ECG arrhythmia classes.

Any ECG classification system's ability to accurately and consistently identify the different elements in the ECG signal is essential to its functionality. The majority of existing research has concentrated on detecting only a few specific arrhythmia classes. The selection of hybrid features and use of deep learning techniques have substantially improved classification accuracy [24, 28, 35], with a maximum of 6 classes classified by [33]. Contemporary methodologies for ECG analysis employ hybrid feature extraction integrated with advanced deep learning frameworks. The key objective of the proposed research is to categorize greater number of heart arrhythmias with increased performances. In general, classification accuracy tends to decrease as the number of ECG signal classes increases. This highlights an opportunity to identify an optimal feature set capable of discriminating a larger number of cardiac conditions while maintaining high classification performance.

A detailed study was done by the authors in this topic, report made and published separately as a review work in [27]. When various literature was surveyed it was found that in addition to morphological features, ECG signals are often characterized using statistical measures, wavelet-based parameters, and fast Fourier transform (FFT)–derived features to support the final classification task. Consequently, a feature set that is optimal for one classification method may not be ideal for another. Identifying the most suitable features for a given classifier is challenging due to the complex and often unknown relationships among different features. Therefore, one of the primary objectives of the present research is to accurately generate a rich set of features from ECG signals and then find out the optimum set of features which provide enhance classification performance. Most of the previous authors have worked on to classify 5 arrhythmias. So, the proposed methodology is designed to classify greater number of cardiac arrhythmias. ECG classification can be performed using a range of methodologies, including conventional statistical classifiers, artificial intelligence–driven models, and deep learning models, such as convolutional and recurrent neural networks (RNNs), that are capable of learning complex temporal dependencies and morphological characteristics from the signals. This paper presents a deep Long Short-Term Memory (LSTM) network designed to improve classification performance and accurately identify 7 distinct types of ECG arrhythmias.

3. Materials and Methods

A flow diagram representing the general process for classifying ECG arrhythmias is displayed in Fig. 2.

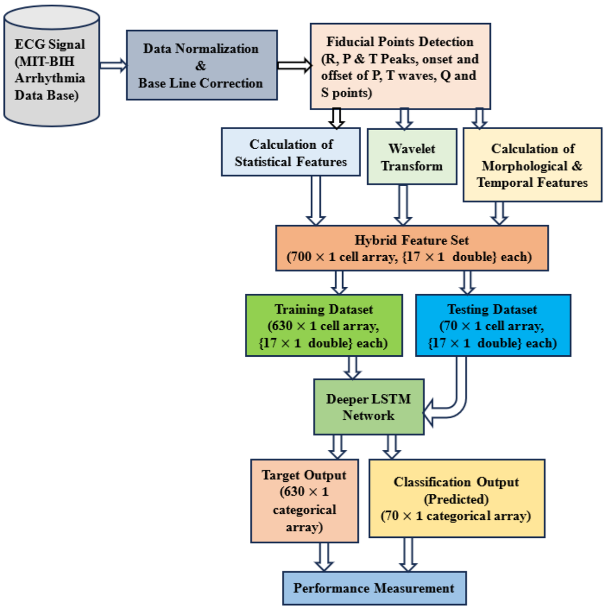


Fig. 2. The methodology proposed for ECG beat classification.

It includes steps like data set formation of various classes of ECG, data normalization and base line correction, fiducial points detection to enable identification of QRS complex, P and T waves present in the ECG. Morphological, temporal, statistical and wavelet features were calculated once the fiducial points are detected and a set of hybrid features were prepared. Lastly, LSTM network training and testing was performed using a chosen feature set for the classification task. Several performance parameters were used to assess the classifier's capabilities. Each step is explained below in detail.

3.1 ECG Signal Data Acquisition and Collection Procedures

The dataset was obtained from the MIT-BIH ADB reflecting various cardiac states applied in the training and performance evaluation of the presented classifier. The MIT-BIH ADB was created by digitizing the ECG signals of various patients sampled at 360 Hz and band passing them at 0.1 to 100 Hz using a band pass filter recorded at an 11-bit resolution over a 10mV. The dataset provides 116137 QRS complexes [26].

Table 1 summarizes the composition of dataset for the proposed work. ECG arrhythmia classification was carried out using signals recorded in the Modified Limb II (MLII) configuration.

Table 1. Composition of Dataset.

Class	Record No. and No. of Beats Taken						Total
N	Record No.	103	105	116	122	201	05
	No. of Beats	20	20	20	20	20	100
L	Record No.	109	111	207	214		04
	No. of Beats	25	25	25	25		100
R	Record No.	118		124			02
	No. of Beats	50		50			100
/	Record No.	107		217			02
	No. of Beats	50		50			100
A	Record No.	209					01
	No. of Beats	100					100
V	Record No.	106	116	119	200	213	05

	No. of Beats	20	20	20	20	20	100
E	Record No.	207					01
	No. of Beats	100					100

A brief description of the various ECG beat types utilized in the suggested classification task is provided below:

N Beat: In normal ECG rhythm P, QRS and T Waves are present. Heart rate is observed to lie between 55 and 105 beats/min, and the PR peaks span from 110 to 200 milliseconds (ms). *L Beat:* A delay in activation is observed in the left ventricle, not in the right, is the cause of the compression of the left ventricle. Prolongation of the QRS complex beyond 120 ms is noted. *R Beat:* The ECG signal's QRS complex shows an extra diversion, indicating that the right ventricle depolarizes more slowly after the left ventricle depolarizes quickly. */ Beat:* RR interval becomes longar than normal ECG beats. *A Beat:* Early heartbeats that begin in the atria are indicative of it. APCs are generated when the sinoatrial node fires more slowly than other atrial regions, allowing ectopic atrial depolarization, which causes an early beat. Normally, the sinoatrial *(*SA*)* node guides the pulse during sinus rhythm.

V Beat: It is characterized by a wider QRS complex which is usually at least 120 ms, ST segment and T wave showing discordant polarity. *E Beat:* The condition presents with a wide, morphologically abnormal QRS complex, following a pause in the normal rhythm which causes greater value of RR interval between two consecutive ECG beats, indicating a failure of the heart's normal conduction system.

3.2. Normalization and Base Line Adjustment

Normalization of the acquired experimental data was done using Equation 1. Since the acquired data was significantly higher than the reference zero base line, it was adjusted for base line using equation 2.

$$\mathrm{ECG} = \frac{\mathrm{ECG}}{|\mathrm{ECG}_{\mathrm{max}}|} \qquad (1)$$

$$\mathrm{ECG} = \mathrm{ECG} - \mathrm{mean}(\mathrm{ECG}) \qquad (2)$$

3.3. Fiducial Point Detection

Fiducial points are the distinct points, specifically the beginning, apex, and ending of the P–QRS–T waveform components present in the ECG, and used to extract waveform features which represents some sort of ECG arrhythmias. Location of these points are required to calculate the height of the R, P and T peaks. Location of these points are also needed to calculate RR interval, QRS duration, and PR interval as temporal features. The morphological features like height of the peaks and temporal features provide the foundation for differentiating between normal and abnormal ECG rhythms as these features change with type of abnormality. The signals are impacted by a number of low frequency disturbances, such as PLI, which shares frequency characteristics with QRS complexes, high frequency muscle noise, and BLW. The ECG signal must be pre-processed to lower these disturbances in order to reliably distinguish different peaks. Four processes, namely filtering, derivative calculation, squaring, and R-peak detection, are involved in the detection procedure.

3.3.1. Filtering

The energy associated with the QRS complex was maximized using the desired pass-band of 4–15 Hz. A BPF was employed to automatically remove low-frequency interference and high-frequency noise components, which was created by cascading the LPF and HPF [17]. As a result, bandpass attenuated both high and low frequency signals while permitting the analysis of specific frequencies to determine the characteristics of a QRS complex.

3.3.2. Derivative Filter

The derivative block receives the noise-free ECG data in order to determine the QRS complex's slope.

3.3.3. Squaring Operation

To improve the comparatively high frequency QRS complex, the resulting signal was subjected to a squaring operation. To smooth the output, an integration is performed using a sliding window because the squaring operation results in several peaks occurring over the duration of a single QRS waveform. The chosen window length was N=30 for a sampling frequency of 360 Hz.

3.3.4. R, P and T-peak Detection

The high frequency QRS was subjected to hard thresholding with the purpose of removing the irrelevant noisy peaks. The suggested threshold value is as follows:

$$\text{Threshold} = \text{maximum (s)} \times \text{mean (s)} \qquad (3)$$

Where s is the output obtained after the moving integration filter. The exact position of the R peak was found by determining the maximum point above the threshold on normalized and baseline adjusted data. The Q- and S-wave locations within the QRS wave were then located by searching for minima adjacent to both sides of the identified R peak. The window-based approach was implemented to identify the P- and T-wave maxima after the occurrence of the R peak. On normalized and baseline-adjusted data, A search window was established 200 ms before and 70 ms after the R peak to detect the P and T peaks, respectively. To detect the P-wave beginning and end, minima were located using a backward and forward search from the wave's maximum, constrained by an appropriate search frame. The sole difference between the process for identifying the T and P waves is that for T wave the search window now begins after the location of the R peaks. Once these characteristic points are located, various morphological and temporal features were calculated.

3.4. Wavelet Transform

All samples between two consecutive R-peak were taken as an ECG beat. Eight level Wavelet decomposition using 'db6' wavelet is performed on each ECG beats to form a set of wavelet-based features. The variance of detail coefficients at each level was taken to form a set of wavelet-based features.

3.5. Statistical Features

Mean, standard deviation and energy of each ECG beats (normalized and base line corrected) were taken to form a set of 3 statistical features.

3.6. Hybrid Feature Selection

The purpose of this step was to choose the signal's distinctive properties to achieve better performance in identifying and categorizing arrhythmic events. The accuracy of classification of ECG beats depends upon how accurately fiducial points are detected. In certain classes of abnormality, the detection of various fiducial point may not be accurate and may reduce the classification accuracy. In order to overcome this problem, wavelet features were also included along with morphological and temporal features to form a feature set to classify any ECG beats of any class. In the proposed work morphological, temporal, wavelet along with statistical parameters were calculated and incorporated to constitute a feature set to classify ECG beats. One of the objectives of this proposed work was to find out a set of hybrid features which increases the performance of the classifier. Various set of features were trained and tested and a comparison was made though it is not being reported here, to find which hybrid set of features provides increased classification performance. Among the several feature sets attempted for classification, the best results are obtained with a feature set of 17 features (3 morphological, 3 temporal, 8 wavelet, and 3 statistical) from each unique heartbeat of the ECG signal.

Table 2. 17 Extracted features.

Features-Numbers	**Characteristic Features**
Morphological - 3	R, P and T peak values
Temporal - 3	RR interval, QRS duration, PR interval
Wavelet - 8	Variance of the wavelet detail coefficients at every level after performing an eight-level decomposition
Statistical - 3	Energy, mean and standard deviation

3.7. Deeper LSTM Network

A deeper LSTM network was created and trained to categorize sequence data. Sequence data can be entered into an LSTM network, which then uses the discrete time steps of the sequence data to generate predictions. Here, each ECG beat was taken as a time sequence and at output corresponding label was produced. From each beat 17 hybrid features were extracted as shown in Table 2. A deep LSTM network was created in order to train and test the acquired ECG data. Each ECG beat was characterized by the value and the quantity of features obtained from extraction, 17 features within the framework of the proposed approach. The data set contained 700 ECG beats, 100 from each class of beats. The training and testing dataset was evaluated using tenfold cross-validation. In each fold 630 beats were used for training, almost 90 from each class and 70 beats were used for testing, almost 10 from each class. Table 1 shows the data sets used in the present work.

The training data XTrain takes the form of a cell array consisting of 630 sequences of length one and dimension 17. The 630 × 1 categorical array of labels "1","2",..., "7" that correspond to the 7 distinct classes of ECG beats is the target output (y), y = 1 for each normal class of ECG beat, y = 2 for each L class of beat, y = 3 for each R class of beat, y = 4 for each / class of beat, y = 5 for each A class of beat, y = 6 for each V class of beat and y = 7 for each E class of beat. XTrain's entries are 17-row matrices, with one row representing each feature and a column representing a single time step.

3.7.1. The Proposed Architecture of the Deep LSTM Network

In the context of sequence-to-label classification, an LSTM network was developed using a layer array comprising a sequence input layer, a fully connected layer, a SoftMax layer, and a classification output layer. The dimensionality of the input layer was defined by the feature vector length, while the size of the fully connected layer was determined by the count of target labels. To enhance network depth, an additional LSTM layer with the output mode set to *sequence* was introduced prior to the final LSTM layer. The final LSTM layer employed the last output mode, with an appropriate number of hidden units specified. An 8x1 layer array containing layers for sequence-to-label categorization using an LSTM network was used in this work is shown in Fig. 3 and discussed below:

1. A sequence input layer with dimension 17, which corresponds to the features count, is created.
2. 125 hidden units fixed in the first LSTM layer. The hidden units in an LSTM layer determine the memory capacity and learning power of the network. They act as internal memory cells that capture patterns across time steps in sequential data.
3. 20% dropout rate was fixed in the dropout layer for the first LSTM layer. In order to avoid overfitting and improve the model's capacity for generalisation, dropout regularisation was used in LSTM networks, particularly when dealing with complicated sequential data like text, voice, or ECG signals.
4. 100 hidden units fixed in the second LSTM layer to make proposed LSTM network deeper.
5. 20% dropout rate in the dropout layer for the second LSTM layer.
6. Fully connected layer equal 7 was created, which is equal to the number of arrhythmias to be classified. The fully connected layer in an LSTM network converts learned sequential features into the final output values or class scores, enabling prediction and classification.

7. A SoftMax layer is used at the end of an LSTM network when the problem is classification, especially multi-class classification (e.g., ECG arrhythmia classes, sentiment categories, activity recognition, etc.). A SoftMax layer is taken in an LSTM network because it converts the LSTM output into normalized class probabilities, enabling final decision-making for classification tasks.
8. Classification output crossentropyex, is created. Cross-entropy is a commonly used loss function for classification tasks, particularly when SoftMax is employed for multi-class outputs or Sigmoid for binary classification. It quantifies the discrepancy between the true class labels and the predicted probability distribution.

Training of the LSTM model employed Adam optimization and backpropagation. A regularization value of 0.1×10^{-3} was used in training, along with learning rates of 1×10^{-3}. The batch size used by the LSTM model was the same as the quantity of features. The categorical cross-entropy was used as a loss function for performance optimization. The LSTM network was trained and evaluated over a maximum of 200 epochs. The dataset was divided into ten subsets, and tenfold cross-validation was applied to ensure robust training and testing. In each fold 630 beats were used for training, almost 90 from each class and 70 beats are used for testing, almost 10 from each class. Therefore, each procedure that checks a distinct subset of the actual data had ten rounds. In each round (fold) of cross validation trained network was tested with 10 beats from each class which were not involved in the training phase in that fold. A class was represented by the concerned beat (either N, L, R, APB, /, V, or E) if the predicted output during the test meets the target. If the predicted output did not match the target, a beat was unclassified. The final step in assessing statistical performance is to take the mean of the tenfold cross-validation results (Table 4).

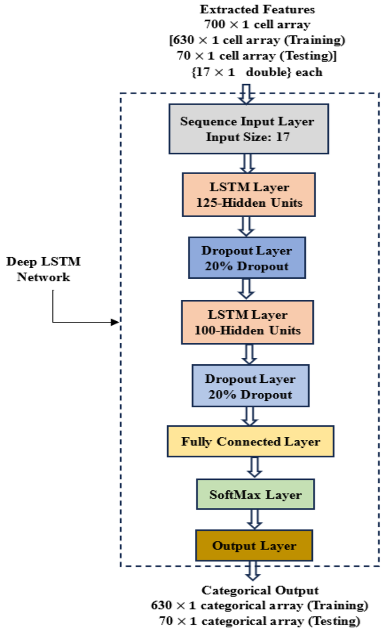


Fig. 3. Proposed architecture of deep LSTM network.

4. Results and Discussion

Experiments were conducted on a system equipped with an AMD Ryzen™ 5 5500U processor (2.10 GHz), Radeon™ Graphics, 16 GB RAM, and a 500 GB SSD using the MATLAB 19 package. ECG signals from MIT-BIH ADB were imported in '.mat' file format to MATLAB 2019 environment for the experiments according to composition of dataset shown in Table 1. Fig. 4 shows the ECG recording belonging to normal class (N) and consists of record of patient number 103, 105, 116, 122 and 201 selected from MIT-BIH ADB for preprocessing stage. Preprocessing and fiducial point detection results for all class of ECG are not shown in the figures, Only the results corresponding to the normal (N) class are shown in Figs. 4–11.

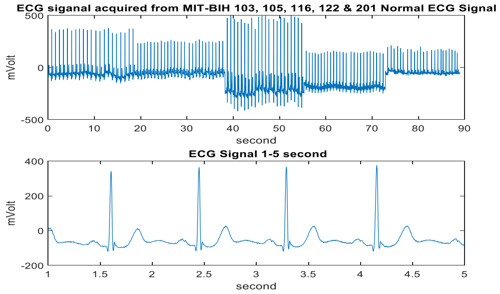


Fig. 4. ECG signal (N Class) acquired from MIT-BIH ADB.

Fig. 5 shows the normalized and baseline corrected ECG signal for N class. The ECG signals selected were de-noised using low-pass and high-pass filtering operations. The waveform after LPF is shown in Fig. 6 and after HPF in Fig. 7 for N class.

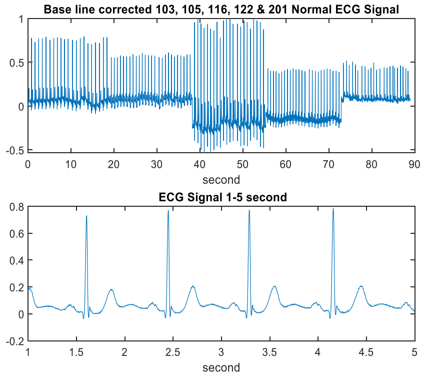


Fig. 5. Baseline corrected and normalized ECG signal (N Class).

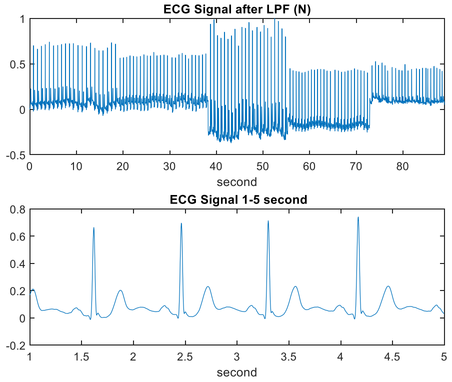


Fig. 6. ECG signal after passing into LPF (N class).

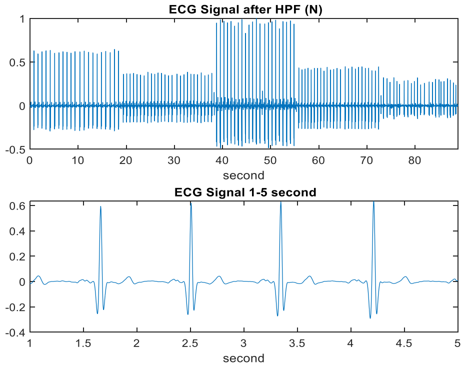


Fig. 7. ECG signal after passing into HPF (N class).

Fig. 8 shows the signal obtained after derivative filter for N class.

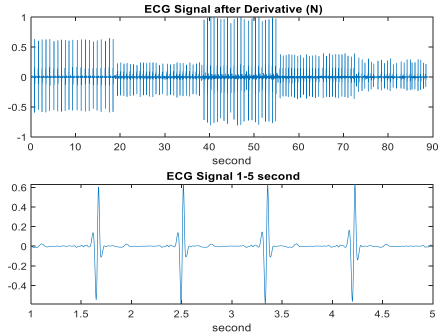


Fig. 8. ECG signal obtained after derivative filter (N Class).

The ECG signal after squaring operation is shown in Fig. 9.

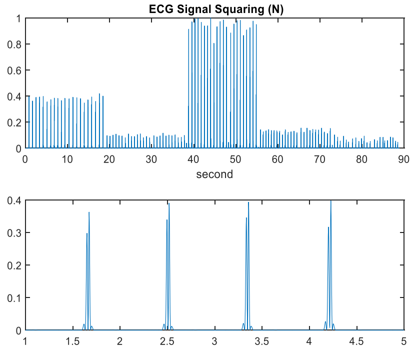


Fig. 9. ECG signal after squaring operation (N Class).

The ECG waveform after averaging operation is shown in Fig. 10.

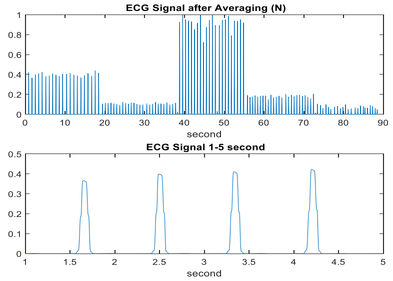


Fig. 10. ECG signal after averaging operation (N Class).

Fig. 11 shows the detected R peaks together with the Q and S points and the P and T wave peaks.

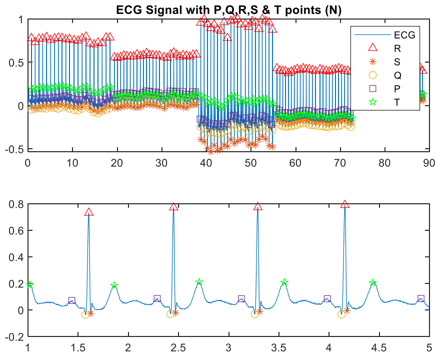


Fig. 11. ECG signal with detected R peak, S & Q points, P and T peaks (N Class).

These fiducial points are located for all 7 classes of arrhythmias according to the data composition shown in Table 1 but not shown in the figures, as only the results obtained for N class was shown in Figs. 5-11. Once fiducial points are located then various morphological and temporal features were calculated for all 7 classes of arrhythmias as per composition of the dataset shown in Table 1. For morphological features R, P and T peak values, for temporal features RR interval, QRS duration, PR interval was calculated.In order to calculate statistical and wavelet features of each beat of ECG, all samples between two consequent R peak were taken as a single ECG beat. Values of 17 features extracted for normal class (N) are shown in Table 3 for the first five ECG beats, for the demonstration purpose only, though 17 features per beat for all classes are taken for classification purposes. The deep LSTM model was developed using the MATLAB 19 package. To evaluate the deep LSTM network performance, the following parameters were computed: overall accuracy (Multiclass), recall, precision, and F-score [24].

$$\text{Recall (R)} = \frac{\text{TP}}{\text{TP+FN}} \tag{4}$$

$$\text{Precision (P)} = \frac{\text{TP}}{\text{TP+FP}} \tag{5}$$

$$\text{F} - \text{score (F)} = 2\frac{\text{P} * \text{Se}}{\text{P+Se}} \tag{6}$$

$$\text{Overall Accuracy (MCA)} = \frac{\sum(\text{TP+TN})}{\sum(\text{TP+FP+TN+FN})} \tag{7}$$

Where:

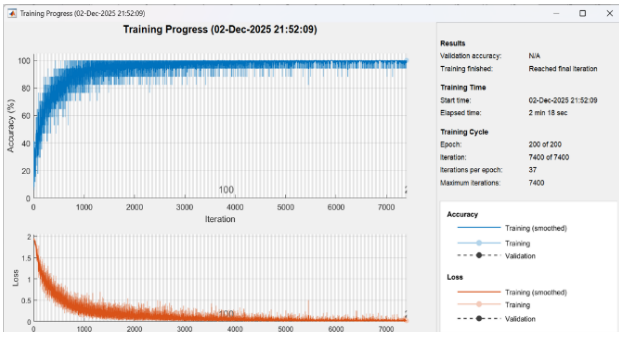
TP (True Positive): Classifies true as true
FP (False Positive): Classifies false as true
TN (True Negative): Classifies false as false
FN (False Negative): Classifies true as false

The TP, FP, FN, and TN values for each class were calculated with the help of confusion matrix.

Table 3. The 17 extracted features from 5 beats of N class.

Features	**Feature Values**	**Beat -1**	**Beat- 2**	**Beat- 3**	**Beat- 4**	**Beat- 5**
Morphological	R Peak Value	0.7768	0.7702	0.7702	0.7718	0.7885
	P Peak Value	0.0807	0.0707	0.0857	0.0841	0.0841
	T Peak Value	0.189	0.184	0.209	0.2073	0.204
Temporal	RR Interval	0.836	0.8444	0.8389	0.8667	0.925
	QRS Duration	0.05	0.0528	0.05	0.05	0.0556
	PR Interval	0.1667	0.1694	0.1639	0.1639	0.175
Statistical	Energy	5.3026	5.187	5.916	5.9249	6.4605
	Mean	0.0699	0.0746	0.0815	0.0813	0.0833
	Standard Deviation	0.1128	0.1072	0.1141	0.1112	0.1115
Wavelet	d1 variance (1.0e-04) *	0.1089	0.0601	0.0729	0.0599	0.554
	d2 variance (1.0e-03) *	0.5858	0.4903	0.6972	0.5089	0.2449
	d3 variance	0.0193	0.0179	0.021	0.0176	0.0155
	d4variance	0.1848	0.1501	0.1648	0.1557	0.1712
	d5 variance	0.1131	0.3291	0.2357	0.1275	0.1092
	d6 variance	0.2654	0.2415	0.2992	1.1399	0.3014
	d7 variance	0.5843	0.4887	0.6267	0.5626	0.6361
	d8 variance	3.7189	3.1407	4.1373	3.0826	0.9243

The training process converges steadily in all fold of cross validation but here only first and tenth fold of cross validation progress is illustrated in Figs. 12-13 respectively.

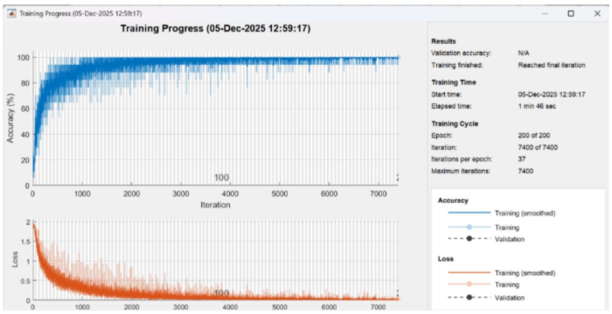


Results
Validation accuracy: N/A
Training finished: Reached final iteration

Training Time
Start time: 02-Dec-2025 21:52:09
Elapsed time: 2 min 18 sec

Training Cycle
Epoch: 200 of 200
Iteration: 7400 of 7400
Iterations per epoch: 37
Maximum iterations: 7400

Fig. 12. Training progress during first fold.



Results
Validation accuracy: N/A
Training finished: Reached final iteration

Training Time
Start time: 05-Dec-2025 12:59:17
Elapsed time: 1 min 46 sec

Training Cycle
Epoch: 200 of 200
Iteration: 7400 of 7400
Iterations per epoch: 37
Maximum iterations: 7400

Fig. 13. Training progress during tenth fold.

The CPU took an average of 128 seconds per fold to complete training of the ECG dataset at a learning rate of 1×10^{-3}. Training progress of other fold of cross validation are not reported in this paper. Table 4 shows statistical performance of a proposed classifier obtained on MIT-BIH ADB by taking average over all 10-fold and summarizes the performance of the model where R, P and F-score is shown for each class. The overall classification accuracy (multiclass-MCA) is also shown in this table. The proposed classifier averaged 99.43%, 99.44%, 99.45%, and 99.41% in terms of MCA, P, R, and F, respectively.

Table 4. Statistical performance of a proposed classifier on ECG data as obtained by average over all 10-fold.

Heartbeat Type (MITBIH)	**P (%)**	**R (%)**	**F (%)**	**MCA (%)**
/	99.09	100	99.52	**99.43**
A	100	100	100	
E	100	100	100	
L	97.86	100	98.86	
N	100	96.64	98.41	
R	99.09	100	99.52	
V	100	99.08	99.57	
Average	**99.44**	**99.45**	**99.41**	

The performance comparison for number of arrhythmias classified by various authors is shown in Table 6 and in Fig. 14. Based on the AAMI standard [36], heartbeats are classified into 5 super classes, as shown in Table 5.

Table 5. ECG Beat classification as per AAMI standard.

ANSI/AAMI	**MIT-BIH heart beat classes**
N	Normal beat (N) Right bundle branch block beat (R) Atrial escape beat (e) Nodal (junctional) escape beat (j)
S	Atrial premature beat (A) Aberrated atrial premature (a) Nodal (junctional) premature beat (J) Supraventricular premature beat (S)
V	Premature ventricular contraction (V) Ventricular escape beat (E).
F	Fusion of ventricular and normal beat (F)
Q	Unclassified beat (Q)

This is clear from Table 6 and figure 14 that the proposed work classified 7 cardiac arrhythmias which is greater than the number of arrhythmias classified by the mentioned author in Table 6. Comparative evaluation with cutting edge techniques indicates that the proposed approach achieves improved performance. The Comparative analysis is shown below in Table 6 and 7.

It is evident from Table 7, performance in terms of recall, precision and multiclass accuracy of proposed work is also highest. The hardware required and processing time is less compared to other methods. Proposed work is able to achieve more than 99.41% performance as measured by MCA, P, R, and F with less hardware and less processing time required for the categorization of ECG beats, which shows proposed work implementation is easy, less costly and time saving with excellent performance in classifying 7 mentioned class of ECG beats.

Table 6. Performance comparisons for number of arrhythmias classified.

Authors	**No. of Arrhythmias Classified (AAMI /MIT-BIH standard)**
[8]	4 AAMI
[11]	5 AAMI
[14]	6 MIT-BIH
[15]	5 AAMI
[24]	5 AAMI
[28]	3 AAMI
[29]	5 AAMI
[30]	3 AAMI
[32]	3 MIT-BIH
[33]	5 MIT-BIH
[34]	5 AAMI
[35]	5 MIT-BIH
***Proposed**	**7** MIT-BIH

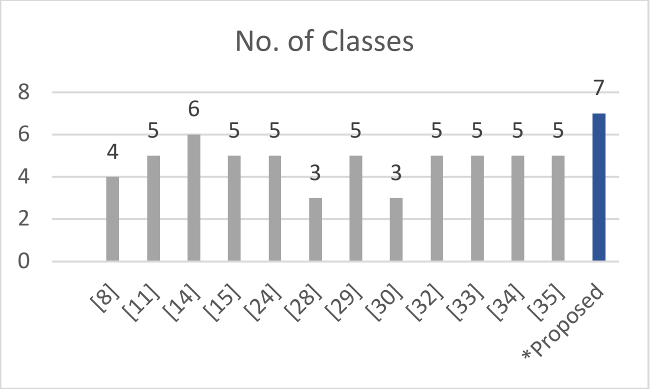


Fig. 14. Comparison for number of arrhythmias classified.

Table 7. Performance comparisons obtained.

Authors	**MCA (%)**	**P (%)**	**R (%)**	**F (%)**
[8]	93	82	80	80.99
[11]	99.3	99.32	--	--
[14]	87.01	65.54	63.47	64.49
[15]	98.9	--	98.9	--
[24]	98.36	96.5	93.03	94.55
[28]	99.26	97.35	96.03	96.69
[29]	99.08	99.11	98.82	98.96
[30]	95	94.3	92.5	93.39
[32]	98.18	--	91.9	--
[33]	98.66	98.92	93.88	96.33
[34]	95.9	95.2	95.1	95.15
[35]	99.14	--	--	94.69
***Proposed**	**99.43**	**99.44**	**99.45**	**99.41**

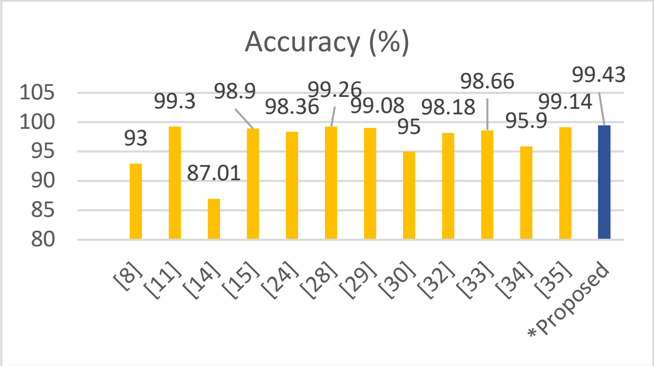


Fig. 15. Performance comparison for overall accuracy achieved.

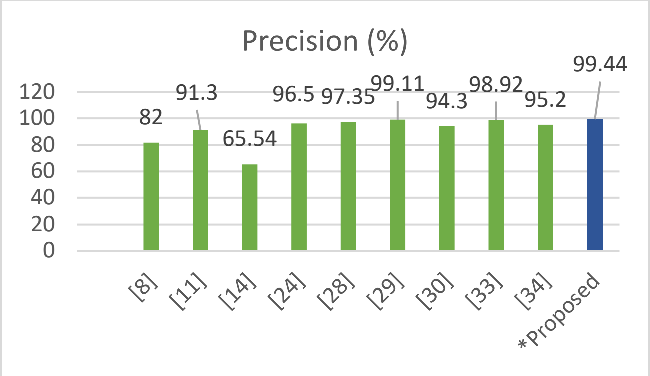


Fig. 16. Performance comparison for overall precision achieved.

Hardware required and processing time is less when the proposed method is evaluated against other techniques, because of smaller size of the data base and the training with the extracted 17 features from each beat and not with whole raw data (360 samples each beat).

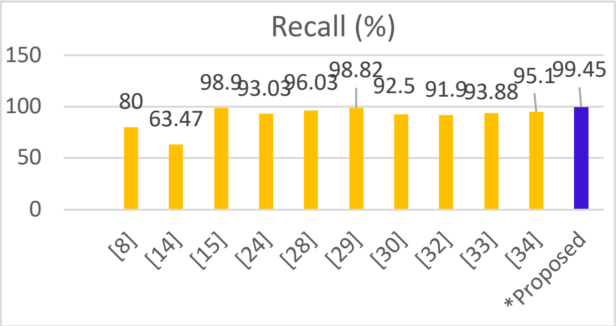


Fig. 17. Performance comparison for overall recall achieved.

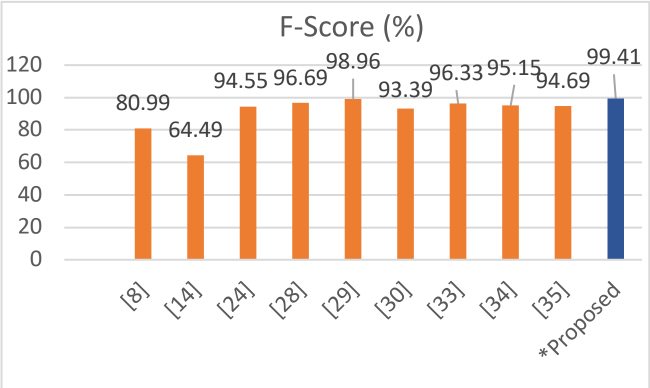


Fig. 18. Performance. comparison for overall F-score achieved.

5. Conclusion and Future Scope

Contemporary ECG analysis methods increasingly adopt hybrid feature sets due to their ability to improve overall performance metrics. Lower classification accuracy is observed for rare arrhythmia types. The main objective of the present work was to expand the range of cardiac conditions that can be accurately detected and reduce the hardware and processing time requirement. This work making significant contribution for the enhancement of cardiac disease categorization by classifying 7 number of cardiac arrhythmias with enhanced performance. The time required to process the signal is very less as compared to most of the existing method.

In future a greater number of categories (more than 7) of ECG signals can be taken up for the classification task. The secured real time health care monitoring system based on ECG can be developed for telemetry application using cryptographic techniques.

Conflict of Interest

Regarding the publication of this work, there are no conflicts of interest.

Funding Statement

No funds or any financial support was received for preparing this manuscript.

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