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Hybrid convolutional neural network-long short-term memory combined model for arrhythmia classification

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ABSTRACT

The automated examination of electrocardiogram (ECG) signals holds significant importance within the medical field for managing various critical cardiac conditions. Identifying cardiomyopathy and arrhythmias is presently recognized as a challenging endeavor. While machine learning techniques have garnered substantial attention for categorizing these patterns, a predominant focus has been on the classification of arrhythmias. However, existing studies have overlooked instances where arrhythmia leads to cardiomyopathy, a specific cardiac disease scenario. In our research, we introduce an innovative method aimed at distinguishing between cardiomyopathy and cardiomyopathy accompanied by arrhythmia by employing a convolutional neural network (CNN-based) model. This novel approach fills the gap in existing literature by addressing the critical need to classify cases where arrhythmia induces cardiomyopathy, thereby presenting a potential advancement in accurately identifying and managing complex cardiac conditions. The proposed model uses convolution-based CNN model for feature extraction and combines these features with temporal features. Further, a CNN combined long short-term memory (CNN-LSTM) model is presented for classification where CNN models help to obtain the spatial information and LSTM helps to retain the temporal information resulting in improved classification accuracy. the experimental analysis is carried out into two phases where we have classified the rhythms and arrhythmias.

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1. INTRODUCTION

In recent years, cardiovascular related health issues have become life threatening disease for human health. According to World Health Organization (WHO), 30% of deaths are caused due to cardiovascular diseases (CVDs) [1]. According to the CVD stands as the primary contributor to human mortality, accounting for 31% of global deaths in 2016. Of these fatalities, 85% were attributed to heart attacks. The yearly economic impact of CVD on Europe and America is approximated at €210 billion and $555 billion, respectively. Moreover, post coronavirus disease 2019 (COVID-19), the heart related health issues have increased drastically. The traditional methods to diagnose the CVD require medical history of individual patient's and several medical examinations. Further, the obtained results need to interpreted according to the certain set of standard medical parameter to classify the disease. The traditional rule-based diagnostic approach often proves ineffective when handling extensive sets of varied data, demanding substantial analysis and medical proficiency to attain satisfactory diagnostic accuracy. This challenge becomes more evident in regions where the scarcity of medical professionals and clinical resources is prevalent, particularly in developing nations. Hence, there is a growing necessity for a dependable, automated, and cost-effective system to facilitate monitoring and diagnosis.

The electrocardiogram (ECG) signal has been used widely by the clinicians and experts to analyze the activity of heart [2]. However, the manual analysis of ECG signals is a time-consuming task and it remains a tedious task to interpret all reading through manual inspection. The ECG signal helps to represents the heart's electoral action therefore it is known as potential solution for various biomedical applications such as pulse measurement, heart beat analysis, and heart rate abnormality analysis. To obtain these outcomes precisely, researchers have suggested to adopt the automated approach by using computer aided diagnosis (CAD) systems for efficient analysis of ECG signals [3]. The conventional rule-based diagnostic approach often proves ineffective when handling extensive sets of varied data, demanding substantial analysis and medical proficiency to attain satisfactory diagnostic accuracy. This challenge becomes more evident in regions where the scarcity of medical professionals and clinical resources is prevalent, particularly in developing nations. Hence, there is a growing necessity for a dependable, automated, and cost-effective system to facilitate monitoring and diagnosis

In this domain, several tasks need to be performed to achieve the desired output in different stages such as ECG signal filtering [4], Feature extraction and classification [5], [6]. The ECG signal filtering takes place in first stage because generally during the capturing these signals, the originality of signals is contaminated due to several other noisy data such as electrode movement and muscle artifacts. Processing these noisy signals may lead to generate inaccurate analysis. Therefore, several methods have been introduced to handle this issue such as wavelet transform [7], Weiner filter [8], Kalman filter [9], and deep convolution neural network [10]. Similarly, feature extraction and classification methods are also introduced to detect and classify the heart related and other cardiovascular diseases. Several methods have been introduced for robust feature extraction and classification such as multidimensional feature extraction and selection [11], continuous wavelet transform with CNN [12] and many more as discussed in [5] and [13]. The current growth of deep learning methods has gained tremendous attention in classification tasks in this domain of biomedical applications. Shaker *et al.* [14] developed a generalized CNN based model for ECG classification by using generative adversarial networks. Atal and Singh [15] introduced optimized deep CNN architecture for Arrhythmia classification.

Several works have been discussed to improve the accuracy of CNN classification however, the performance of these systems is affected due to several factors such as data variability, class imbalance, data interpretably and generalization of these classification models. These issues need to be addressed for efficient utilization of deep learning models for ECG signal processing systems. Generally, the ECG signals are temporal in nature representing the electrical activity of heart. In this scenario, capturing the temporal dynamics plays an important role because the CNN architectures are designed to process the spatial data such as image thus the performance of these systems is affected for temporal data. Similarly, long short-term memory (LSTM) model is considered as promising technique for but it suffers from several issues such as overfitting, handling the sequence length because the traditional LSTM models worked for the fixed length sequence whereas the characteristics of ECG signals vary. However, the combination of these two models has been considered as a promising method for various machine learning tasks because of their nature of learning the complex patterns. Based on this we present a complete deep learning architecture-based solution for ECG classification. The main contribution of this work are as follows: i) the first phase extracts the temporal features which includes mean, max, standard deviation, variance, skewness and kurtosis; ii) in next phase, a deep learning architecture is introduced to extract the deep features which also considers the temporal feature to produce the final feature map; and iii) the obtained feature is further processed through the combined CNN-LSTM architecture to obtain the classification outcome.

This section presents the overview of existing feature extraction, classification where deep learning and machine learning based methods are discussed and identified their contribution and challenges in ECG classification. Sangaiah *et al.* [16] developed a novel approach which is comprised of three steps as ECG filtering, wavelet feature extraction and hidden Markov model (HMM) for arrhythmia classification. The feature extraction model also considers statistical features such as minimum, maximum, mean, standard deviation and median. Mathunjwa *et al.* [17] presented arrhythmia classification approach by using second segment of 2D recurrence plot images of ECG signals. In first stage, atrial fibrillation (AF) and noise data is distinguished. Later, atrial fibrillation (AF), normal, premature AF, and premature ventricular fibrillation (VF) categories were identified. Finally, ImageNet based CNN architecture is used to classify the ECG signal. Abdalla *et al.* [18] introduced a novel CNN architecture which uses four convolution layer, four max pooling layer and three fully connected layers. This method has reported the classification accuracy of 99.84% for MIT-BIH dataset. Kuila *et al.* [19] presented a novel approach which uses morphological filtering for ECG data. Later, extreme learning machine and recurrent neural network models are employed to perform the classification. Wang *et al.* [12] introduced an automated approach for ECG classification with the help of continuous wavelet transform (CWT) and CNN. The CNN model helps to decompose the ECG signal to produce the time-frequency components whereas CNN helps to extract the features from 2D scalogram obtained by time-frequency components. Chen *et al.* [20] reported the issue of imbalanced dataset and memory capability in wearable devices and proposed CNN based hybrid model for ECG classification. the first phase includes data enhancement module where the amplitude of small number of samples is changed combined with the weighted loss function of deep learning model. In next phase, 1D convolution block attention mechanism is used which works as autoencoder to compress the ECG heartbeat signals. Finally, modified 1D lightweight CNN architecture is introduced which uses MobileNet as the base architecture for classification. Alamatsaz *et al.* [21] presented deep learning based approach to classify 8 different types of cardiac arrhythmias and normal rhythms. The pre-processing phase includes resampling and removal of baseline wander. In next phase, an ensemble of CNN and long short-term memory (LSTM) is presented to improve the classification accuracy. Deng *et al.* [22] reported that the traditional ECG devices fail to detect arrhythmia due to the intermittent nature of patient's visit. Therefore, authors introduced a novel approach for wearable devices for cardiac arrhythmia detection. The R-peak detection task is performed with the help of Hilbert transform method and further Haar discrete wavelet transform is used for robust feature extraction. Finally, a hybrid support vector machine (SVM) classifier is presented to classify the normal and abnormal heartbeats. Xia *et al.* [23] reported that the attention mechanisms have gained huge attention in learning based approaches where transformer based models are widely adopted in classification tasks. The transformer architectures are type of encoder–decoder module which contains attention mechanism with fully connected layer. Moreover, authors have reported the data imbalance problem for arrhythmia detection therefore a data augmentation approach is introduced which is based on the transformer and convolution-based generative adversarial network (TCGAN). Goswami *et al.* [24] presented ECG classification approach which includes data pre-processing, filtering as initial stages. In classification phase, a hybrid model is introduced which uses CNN, random forest, SVM and K-nearest neighbor (KNN). Cai *et al.* [25] developed a real-time arrhythmia classification approach by using deep learning approach. his approach includes heart beat segmentation, QRS complex detection. In feature extraction stage, it extracts the ECG-RRR features are extracted based on the heartbeat segmentation.

2. METHOD

This section presents the proposed model for ECG classification. the complete work is carried out into two phases where first stage performs temporal and deep learning-based feature extraction model. Later, a hybrid deep learning classification model is presented for arrhythmia classification. the overall architecture of proposed model is depicted in Figure 1.

According to this work, the complete process is divided into three main stages where first stage focuses on feature extraction phase where temporal deep learning features are extracted. In next stage, we perform feature fusion where both features are combined together to formulate the final feature vector. In next stage, a combined CNN and LSTM model is applied to obtain the final classification.

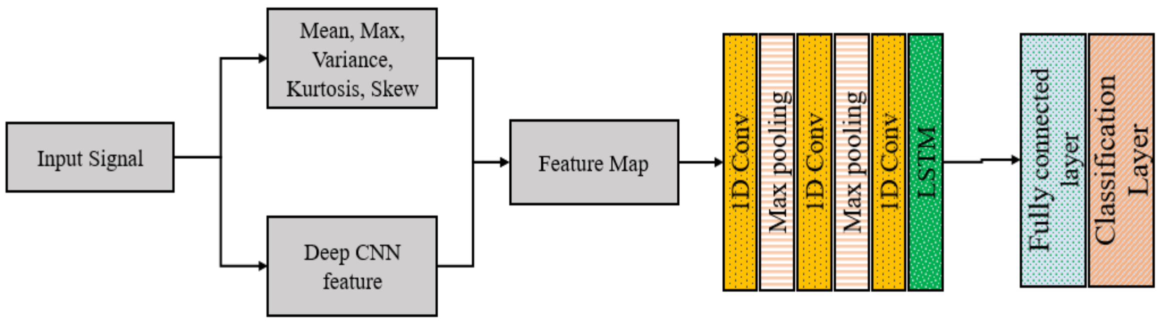

Figure 1. Overall architecture of proposed model

2.1. Feature extraction model

The proposed feature extraction model is a combination of two feature extraction models where first phase considers temporal feature extraction where mean, max, root mean square, standard deviation, variance, skew and kurtosis are computed as presented in Table 1. In next stage, we incorporate a deep learning-based model for feature extraction which generates various feature maps from level layers to high level layers. The convolution layer and pooling layers are employed to obtain the features which helps to generate the robust feature map during intermediate layers. In this work, we have used 1D convolution layer to extract the deep features from ECG signa.

Table 1. Feature extraction type and formula

Feature index	Feature type	Calculation formula
F1	Mean	$F1 = x = \sum \frac{X_i}{N}$
F2	Max	$F2 = \max(x)$
F3	Standard Deviation	$F3 = \sqrt{\frac{1}{N-1}\sum(x-\tilde{x})^2}$
F4	Variance	$F4 = F3^2 - \frac{1}{N-1}\sum(x-\tilde{x})^2$
F5	Skewness	$F5 = \frac{\frac{1}{N-1}\Sigma(x-\tilde{x})^3}{\left[\frac{1}{N-1}\Sigma(x-\tilde{x})^2\right]^{\frac{3}{2}}}$
F6	Kurtosis	$F6 = \frac{\frac{1}{N-1}\Sigma(x-\tilde{x})^4}{\left[\frac{1}{N-1}\Sigma(x-\tilde{x})^2\right]^{2}}$

In next stage, we incorporate a deep learning-based model for feature extraction which generates various feature maps from level layers to high level layers. The convolution layer and pooling layers are employed to obtain the features which helps to generate the robust feature map during intermediate layers. In this work, we have used 1D convolution layer to extract the deep features from ECG signal. These convolution layers have shape of 64×21, 64×7, 256×13 and 256×9 with strides 11, 1, 1, and 1, respectively. Figure 2 depicts the architecture of feature extraction model. The aforementioned model depicts the feature extraction process and once the feature extraction is done both deep learning and temporal features are fused together to generate the final feature map. This feature map is fed to the classification model.

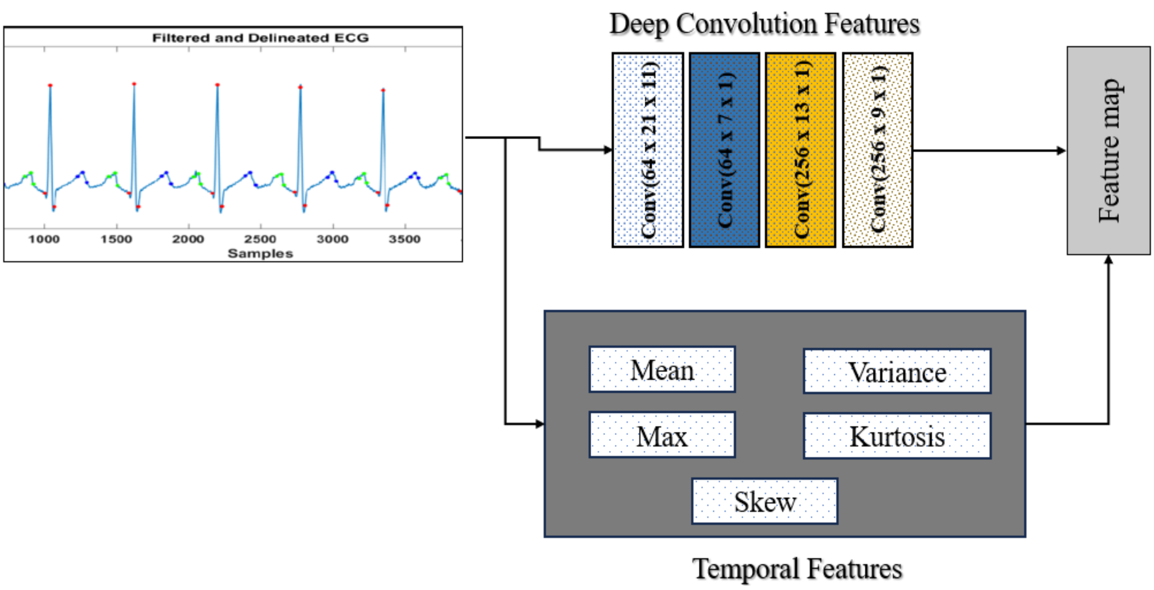

Figure 2. Deep learning and temporal feature extraction

2.2. Classification model

This section describes the proposed approach for classification of ECG signals. As discussed before that the current advancements in deep learning methods have motivated researchers to adopt these methods for classification tasks. However, these models face several challenges such as long-term dependencies of temporal features which can impact the overall accuracy. To overcome this issue, we combine standard CNN classification architecture with BiLSTM classification approach. below given subsections describe the CNN and BiLSTM models followed by the combined classification model.

2.2.1. Convolutional neural network

In this section, we have presented a brief discussion about convolutional neural network which is widely adopted for several classification tasks. The CNN is the type of multilayer perceptron and has been considered as promising technique in deep learning domain. The base concept of this architecture follows the traditional neural network thus it is constructed with the help of neurons, weights and biases. the standard CNN architectures comprise of several layers such as convolutional layers, pooling layer and fully connected layer. The convolution layer is responsible for performing the elementwise multiplication over a given input. The pooling layer is used to down sample the feature maps and it is able to learn the large-scale image features.it requires some activation functions which are used to compute the weighted sum of activation function. Similarly, the fully connected layer is used to compute the class score as the final stage of classification process.

In this work, we have considered ECG signal which is transformed into 1D data vector and expressed as $x = (x_1, x_2, \dots x_{n-1}, x_n, c)$ where c represents the label of corresponding class and $x_n \in \mathcal{R}^{\mathcal{A}}$ represents the HRV features of ECG signal where $\mathcal{A}$ represents the arrhythmia/ECG beat data. The convolution layer helps to obtain the feature map which is represented as f_m, further, filtering operations are employed and the final feature set is represented as (1),

$$hl_i^{f_m} = \tanh\left(w^{f_m} x_{i:i+f-1} + b\right) \tag{1}$$

where hl represents the filtering operation which is performed on each feature map and denoted as (2),

$$hl = \left[hl_1, hl_2, \dots, hl_{n-f+1}\right] \tag{2}$$

and b denotes the bias. According to this approach. the CNN architecture uses ReLU activation function and the obtained output is fed to the pooling layer which produces the down sampled output.

As discussed before, the max pooling operation is employed on the obtained feature map as $\overrightarrow{hl} = \max\{hl\}$ and it generates the most significant attributes. These features are fed to the fully connected layer where we apply soft-max function to produce the probability distribution function of each class to get the final classification. The soft-max is a mathematical function that takes a vector as input and converts its individual values into probabilities, depending on their size.

2.3. Long short-term memory network

Despite of extensive use of CNN based DL architectures, these models face several challenges in various real-time applications because of retaining the long-term dependencies of attributes. Moreover, gradient vanishing also remains a challenging issue therefore researchers have introduced several methods such as recurrent neural network (RNN) but the accuracy remains a challenging task. Therefore, researchers have presented Long short-term memory (LSTM) approach which uses certain memory blocks to recall the historical information that results in reducing the learning error. The LSTM model comprises of several units such as memory cells and multiplicative gates which are used to control the memory blocks. According to this model let x be an arbitrary data sequence expressed as $x = (x_1, x_2, \dots, x_{T-1})$ given as input to the LSTM model. The output for this model is obtained with the help of three different multiplicative units such as input gate, output gate and forget gates. In order to obtain the final output, it follows an iterative process where it uses total T iterations. The operations of various units are expressed as (3).

$$\begin{aligned}
inp &= \sigma(x_t w_{xin} + w_{hin} h_{t-1} + w_{clin} cl_{t-1} + b_{in}) \\
fg_t &= \sigma\left(x_t w_{xfg} + w_{hfg} h_{t-1} + w_{clfg} cl_{t-1} + b_{fg}\right) \\
cl_t &= cl_{t-1} \odot fg_1 + in_{t-1} \odot \tanh(x_t w_{xcl} + h_{t-1} w_{hcl} + b_{cl}) \\
op_t &= \sigma\left(x_t w_{xop} + h_{t-1} w_{hop} + cl_t w_{clop} + b_{op}\right) \\
h_t &= \tanh(cl_t) \odot op_t
\end{aligned} \tag{3}$$

In order to take the advantage of temporal, spatial and long-term information, we have presented the combined model of CNN and LSTM. The complete process is described in next section.

2.4. Hybrid CNN-LSTM

As discussed before, the conventional CNN model encounters several challenges, including issues with ineffective kernels, redundant extraction of similar information by multiple kernels, and imprecise information retrieval. While these networks have the potential to enhance accuracy by extracting additional information, doing so typically necessitates an increase in convolution layers, kernels, and pooling layers. However, this augmentation amplifies the network's load, computational complexity, and susceptibility to overfitting. To address these limitations, LSTM networks have been developed, specifically designed to handle sequence problems with time dependence. The LSTM excels in filtering performance information, merging redundant inputs, and retaining significant features for extended periods via its memory cell. The proposed CNN-LSTM model aims to categorize ECG signals into different categories based on their labelling. The architecture of the proposed CNN-LSTM model for ECG classification comprises an input layer, a Bi-LSTM layer, a fully connected layer, a SoftMax layer, and a classification layer, as depicted in Figure 3.

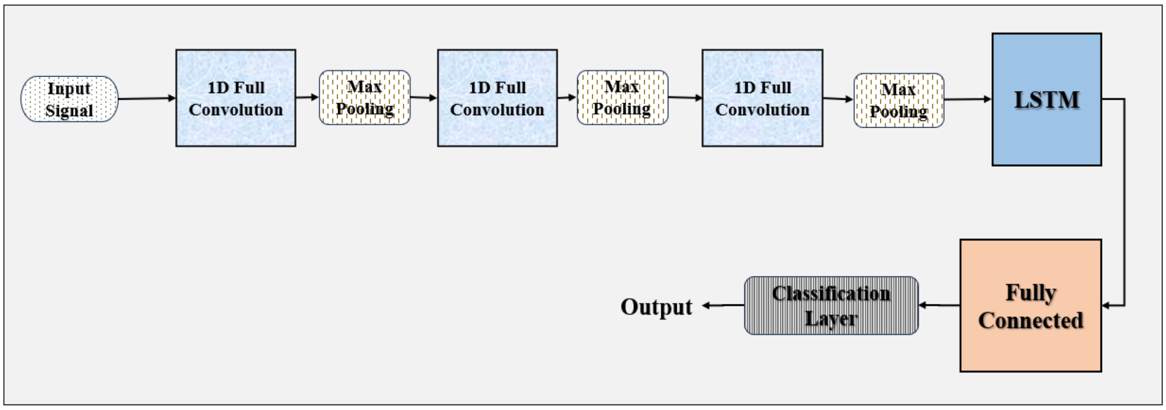

Figure 3. Proposed hybrid CNN-LSTM architecture for arrhythmia classification

2.5. Simulation setup

For experimental analysis of proposed arrhythmia classification approach, we conducted various simulation tests and compared the obtained performance with various existing schemes. The proposed method is developed using python 3 programming language on Visual Studio Code (VS Code) IDE and installed on Windows x64-bit platform. The host system is equipped with 16 GB RAM, and 6 GB GPU from NVDIA 2060 RTX module.

3. RESULTS AND DISCUSSION

This section compares the performance of the suggested approach with other existing categorization approaches and displays the results. features of the dataset which included both normal and aberrant samples used for this experiment. Confusion matrix used to assess how well the suggested model performs in comparison to the current model. Lastly, a comparative study of the suggested model's output using current methodologies was presented.

3.1. Dataset details and performance measurement parameters

The ECG arrhythmia recordings utilized in this study have been sourced from the MIT-BIH arrhythmia database. This database comprises 48 half-hour ECG recordings gathered from 47 patients spanning the years 1975 to 1979. The ECG recordings were taken at a sampling rate of 360 samples per second, resulting in approximately 110,000 ECG beats within the MIT-BIH database, encompassing 15 distinct arrhythmia types, including normal rhythms. However, the specific focus of our investigation is the classification of data into two primary classes. To achieve this goal, in collaboration with expert clinicians, we identified 26 instances of cardiomyopathy and 22 instances of cardiomyopathy with arrhythmia from within the MIT-BIH dataset. The MIT-BIH dataset heartbeats are classified into seven different categories as depicted in Figure 4.

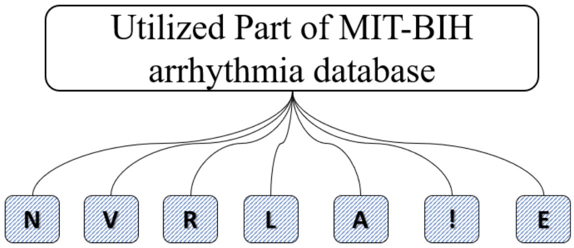

Figure 4. Various heartbeats in the considered dataset

According to this, the N, R, L, A, !, and E represents the premature ventricular contraction, right bundle branch block beat, bundle branch block beat, atrial premature beat, ventricular flutter wave and ventricular escape beat respectively. The evaluation of CNN-LSTM's classification performance is carried out based on confusion matrix. The confusion matrix parameters are mentioned in the Table 2. This matrix allows us to calculate the accuracy, precision, and recall for individual classes as well as an overall assessment for both classes. The resulting performance metrics are then compared against those obtained from support vector machine, neural network, and decision tree classifiers. The representation of the confusion matrix is illustrated:

This allows us to compute a number of performance metrics, some of which are listed in Table 3. The precision measures the proportion of expected positive cases that turn out to be real positives. The percentage of true positive cases that the model successfully detects is measured by recall. Classification accuracy is a summary of classification performance. A high F1-Score is only achieved when precision and recall are high.

Table 2. confusion matrixes

	Positive	Negative
Positive	TP (True Positive)	FP (False Positive)
Negative	FN (False Negative)	TN (True Negative)

Table 3. Performance measurement parameters

Parameter	Formula
Precision	$\frac{TP}{TP+FP}$
Recall	$\frac{TP}{TP+FN}$
Classification Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
F1-Score	$2*\frac{Precision*recall}{Precision+Recall}$

3.2. Comparative analysis

This section presents the comparative analysis of proposed approach where outcome of proposed hybrid model is compared with existing methods as discussed in [26], [27], and [28]. Table 4 demonstrates the obtained performance for each class. Precision, recall and F1-score matrix are used to evaluate the proposed model with existing methods.

This experiment has reported the average precision performance as 0.99, 0.99, 1.00, 1.00, 0.95, 0.98 and 0.99 for N, V, R, L, A, !, and E, respectively. Similarly, we extend this experiment to classify the arrhythmia and non-arrhythmia patients. Therefore, we have identified 26 samples of cardiomyopathy and 22 samples for cardiomyopathy with arrythmia from MIT-BIH dataset. Table 5 provides the sample number belonging to these two classes.

In order to classify these data, we have implemented decision tree, support vector machine, and neural network classifiers and compared the obtained performance with proposed classification scheme. Table 6 shows the obtained performance. This experiment shows that the proposed approach has reported highest classification accuracy of 91.8% whereas decision tree, SVM, neural network has reported 73.15%, 82.52%, and 86.40% respectively.

Table 4. Classification performance analysis

Class	Method	Precision	Recall	F1-Score
N	FrWT [26]	0.96	0.98	0.97
	Sequence to-sequence [27]	0.98	1.0	0.99
	Personalized autoencoder [28]	0.99	1.0	0.99
	Proposed	0.99	1.0	1.0
V	FrWT [26]	0.96	0.93	0.94
	Sequence to-sequence [27]	0.96	0.95	0.95
	Personalized autoencoder [28]	0.98	0.92	0.95
	Proposed	0.99	0.97	0.8
R	FrWT [26]	0.97	0.94	0.95
	Sequence to-sequence [27]	0.97	0.93	0.95
	Personalized autoencoder [28]	0.98	0.98	0.95
	Proposed	1.0	0.99	0.98
L	FrWT [26]	0.97	0.98	0.97
	Sequence to-sequence [27]	0.98	0.95	0.97
	Personalized autoencoder [28]	0.98	0.98	0.97
	Proposed	1.0	0.99	1.0
A	FrWT [26]	0.86	0.77	0.82
	Sequence to-sequence [27]	0.88	0.79	0.83
	Personalized autoencoder [28]	0.89	0.79	0.84
	Proposed	0.95	0.92	0.94
!	FrWT [26]	0.62	0.33	0.49
	Sequence to-sequence [27]	0.67	0.33	0.47
	Personalized autoencoder [28]	0.80	0.36	0.50
	Proposed	0.989	0.85	0.89
E	FrWT [26]	0.88	0.92	0.91
	Sequence to-sequence [27]	0.95	0.88	0.90
	Personalized autoencoder [28]	0.99	0.78	0.87
	Proposed	0.99	0.98	0.95

Table 5. ECG samples considered

Cardiomyopathy samples				Cardiomyopathy with arrhythmia samples			
E	Mg	S	Seg	E	Mg	S	Seg
0614	027, 069, 070, 075, 141	0175, 0189, 0200, 0202, 0222, 0342, 0392, 0444, 0448, 0550, 20231, 20501, 20521, 20531	29, 30, 31	0614	027, 069, 070, 141	0175, 0202, 0420, 0437, 0448, 456, 0448, 0489, 0492, 0549, s20231, 20501	0493, 08, 08, 29, 31

Table 6. Comparative analysis

Classifier	Accuracy	Recall	Precision	F1-Score
Decision tree	0.7315	0.904	0.894	0.8978
Support vector machine	0.8252	0.8193	0.821	0.8129
Neural network	0.864	0.854	0.860	0.8525
Proposed CNN-LSTM	0.918	0.917	0.918	0.9162

4. CONCLUSION

In this work, we have focused on development of an automated approach for real-time arrhythmia detection and classification of rhythms. This article leverages the deep learning for feature extraction and also incorporated the temporal feature extraction model. The obtained features are combined together and fed into the proposed hybrid CNN-LSTM classification where CNN helps to extract the spatial information and LSTM helps to maintain the long-term dependencies of temporal features thus it helps to generate an improved classification model.

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