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A New Approach for Arrhythmia Classification Using Deep Coded Features and LSTM Networks

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Abstract

Background and objective: For diagnosis of arrhythmic heart problems, electrocardiogram (ECG) signals should be recorded and monitored. The long-term signal records obtained are analyzed by expert cardiologists. Devices such as the Holter monitor have limited hardware capabilities. For improved diagnostic capacity, it would be helpful to detect arrhythmic signals automatically. In this study, a novel approach is presented as a candidate solution for these issues.

Methods: A convolutional auto-encoder (CAE) based nonlinear compression structure is implemented to reduce the signal size of arrhythmic beats. Long-short term memory (LSTM) classifiers are employed to automatically recognize arrhythmias using ECG features, which are deeply coded with the CAE network.

Results: Based upon the coded ECG signals, both storage requirement and classification time were considerably reduced. In experimental studies conducted with the MIT-BIH arrhythmia database, ECG signals were compressed by an average 0.70% percentage root mean square difference (PRD) rate, and an accuracy of over 99.0% was observed.

Conclusions: One of the significant contributions of this study is that the proposed approach can significantly reduce time duration when using LSTM networks for data analysis. Thus, a novel and effective approach was proposed for both ECG signal compression, and their high-performance automatic recognition, with very low computational cost.

Keywords: Arrhythmia detection, ECG compression, deep learning, autoencoders, LSTM

1. Introduction

The electrocardiogram (ECG) is a signal that is used to record and monitor the electrical activity of the heart. The collected data is useful because it can be used to control the regularity of heartbeats, and to identify heart diseases, such as arrhythmia, ischemic heart disease, and myocardial infarction [1]. Arrhythmia is a cardiac conduction disorder which may lead to sudden death, and it is characterized by irregular heartbeats, which can be observed in ECG signal recordings [2]. In addition to automated solutions, clinical review of patients by experts is needed for understanding the arrhythmia mechanism [3]. In traditional automated ECG solutions, there are generally two major steps. The first is detection and feature extraction, and the second is classification. Although ECG signal processing is commonly used due to its simplicity and noninvasiveness, automated classification systems impart several challenges. Some of these challenges can be summarized as follows [40, 41]: i) lack of standardization in ECG features and their variability; ii) ECG patterns differ for every subject so that it is difficult to scale them to larger populations, iii) lack of specific rules for ECG classification, and iv) signal waveforms also differ for every subject.

Arrhythmias cause abnormal heart rhythms by affecting the heart muscle electrical system in the form of abnormal electrical impulses. Arrhythmias can be detected and diagnosed by the combination of accurate ECG signal identification and supplementary expert opinion. Therefore, many hybrid solutions have been developed for this detection task and they are described in the literature [38, 50]. Prasad et al. [4] have used nonlinear features of higher order spectra (HOS) to differentiate ECG beats, and have employed k-nearest-neighbor (KNN), classification and regression tree (CART) and neural network (NN) classifiers in the second stage of the solution. Similarly, nonlinear models based upon third-order HOS cumulants and HOS bispectrum were employed, since ECG data contains noise and it is also a nonlinear, nonstationary and non-Gaussian signal [5]. HOS features are preferred inputs to classify ECG signals, as contain the non-linear and dynamic nature of the signals [51]. It is also possible to compute the discrete cosine transform (DCT) coefficients from the segmented beats of the ECG for signal characterization [6].

Convolutional neural networks (CNN), which perform both feature extraction and classification processes with a conventional training stage, are typically used in deep learning studies [7-9, 44]. In the CNN structure, numerous convolutional and pooling layers are cascaded successively to form a deep network for extracting the underlying features of an input. CNN has already been applied to research areas for facial recognition [10, 11] and for computer gaming [12]. Since CNN structures are successful in computationally intensive studies, they are suitable candidates to serve as components for ECG signal recognition mechanisms [13-20, 45, 49]. Acharya et al. [17] implemented an eleven-layer CNN model on segmented ECG signals for the automated identification of shockable and non-shockable ventricular arrhythmias. Correspondingly, CNN can be used at different intervals of tachycardia ECG segments for automated arrhythmia detection [18]. Yildirim et al. [19] used a 16 layer deep CNN model to classify long duration ECG signals.

Long-short term memory (LSTM) [21] networks are another important approach that have been widely used in recent deep learning studies. LSTMs have also been used in the classification of ECG signals [2, 22-24]. Several methodologies have been proposed to improve the performance of LSTM networks. In a recent study, LSTM was combined with CNN to form a hybrid solution for arrhythmia detection, using variable length heartbeats [2]. Tan et al. [24] implemented a LSTM network with CNN to automatically and accurately diagnose coronary artery disease (CAD) from ECG signal recordings. The performance of LSTM based solutions can be improved by using a wavelet sequence at the input of the network [23].

These promising results have motivated investigators to search for improved deep learning-based solutions. Autoencoders (AE) can be utilized for different tasks, such as dimensionality reduction, image processing, hashing, and denoising [25-28]. In one study, a denoising autoencoder (DAE) was used with sparsity constraint in the feature representation of ECG signals [25]. Similarly, stacked or deep AEs can be utilized in multi-layered neural structures for other tasks, such as ECG signal compression with convolutional AEs (CAE) [29]. The use of CAEs is an important development for improving deep-learning based solutions. In these structures, standard convolutional layers of CNNs are used instead of fully connected layers [30].

Existing approaches in the literature are challenged by the need for experts to manage the process of long duration beat recording in Holter systems. The primary motivation of our study was to overcome this challenge by compressing the data and then classifying it. As the compression process requires feasible reconstruction, we designed a high-quality reconstruction paradigm. Thus, high recognition performance was obtained from a low feature size. To achieve this outcome, for the first time in the literature, deep CAE was used for ECG beat compression and classification. Compressed sensing is a good solution to reduce power consumption in data transfer. Sparsity of signals implies the original signals can be reconstructed with low loss ratios by limited data transfer [42]. There will be significant benefits of these systems for wearable technologies as they will be capable of storing large amounts of health data at a lower cost. By using this data they can maintain a long-term ECG record of the subjects.

The contributions of this paper can be summarized as follows: (a) ECG signals are compressed prior to classification. (b) LSTM performance is improved by using low-sized features. (c) Classification results from the deep coded signals implied that the compression operation is efficient and beneficial. (d) For the first time, a deep autoencoder was used for the classification of five different beat signal classes. Previously in the literature, only part of the patient record has been compressed during the classification process [29]. (e) The workload of long duration recordings and manual analysis by cardiologists can thereby be reduced with the system introduced in our study. (f) Coded ECG signals make secure data transmission more achievable.

The remainder of the paper is organized as follows. Materials and methods are presented in Section 2, followed by the details of the proposed deep CAE-LSTM recognition system in Section 3. Experimental results are reported in Section 4. Discussions are given in Section 5. Finally, conclusions and future directions are presented.

2. Materials and Methods

In this study, a new deep CAE-LSTM approach has been proposed for the recognition of arrhythmic heartbeats. In the proposed system, the CAE method was used to compress ECG beats. First, low-dimensional encoded signals were obtained from each ECG trace. A LSTM network model was then constructed to classify the coded signals. Compression of arrhythmic beats and recognition of coded signals were then performed. A total of 100,022 segmented signals belonging to five different ECG beat types were used in the experiments.

2.1. Dataset

In this study, ECG signals were obtained from 48 records of 47 patients from the PhysioNet public database [31]. Each MIT-BIH record was collected with a 360 Hz sampling frequency and 11-bit resolution. The beat labels were independently annotated by multiple cardiologists, whose consensus resolved differences in the diagnoses. Only modified limb lead II signals were used in the study, because these signals are obtained by attaching the electrodes onto the torso, as is the case for Holter recordings. As a result, only appropriate lead signals were selected for quantitative analysis. In the segmentation of ECG pulses, continuous beats within the arrhythmia beat groups were used. Each segment had only one beat type, and this beat consisted of 260 samples. Segments were created to include 99 samples prior to the R peak, and 160 samples following the R peak. In Figure 1, waveforms for five different arrhythmia type classes are given. Table 1 presents the arrhythmia types used in the study and their data size.

Table 1. Arrhythmia types used in the study, and the distribution of data.

Arrhythmia Types		Data size (beat)
Atrial Premature Beat (APB)		2546
Left Bundle Branch Block (LBBB)		8072
Normal Sinus Rhythm (NSR)		75020
Right Bundle Branch Block (RBBB)		7255
Premature Ventricular Contraction (PVC)		7129
	Total Beat:	**100022**

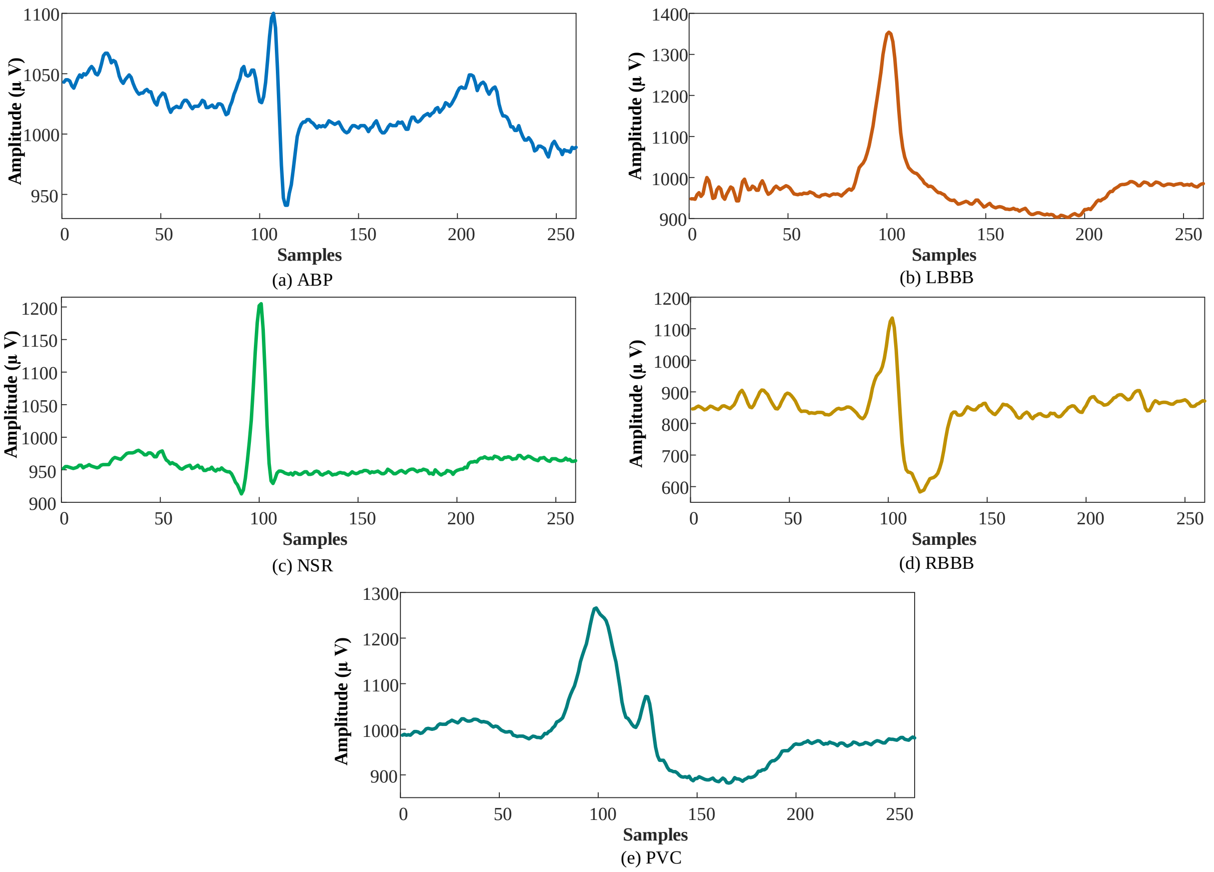


Figure 1. Waveforms of arrhythmia classes: a) ABP, b) LBBB, c) NSR, d) RBBB, e) PVC.

3. The Proposed Deep CAE-LSTM Recognition System

The main purpose of this study is to compress large-sized ECG signals with minimum loss and then to classify them using the compressed signals. As a result, both the storage cost of large amounts of signal data could be reduced and the efficiency of recognition could be increased. Toward these aims, first a deep CAE model has been constructed to compress the data with minimum loss. Then a LSTM model was designed for the recognition of the compressed signals. Thus, a deep CAE and LSTM based approach was proposed for the automatic classification of arrhythmia beats. Initially, ECG beats were compressed with the CAE model, to obtain coded features of each signal. In the next step, coded features were used for classification with a LSTM network. The block representation of the proposed deep CAE-LSTM recognition system is shown in Figure 2.

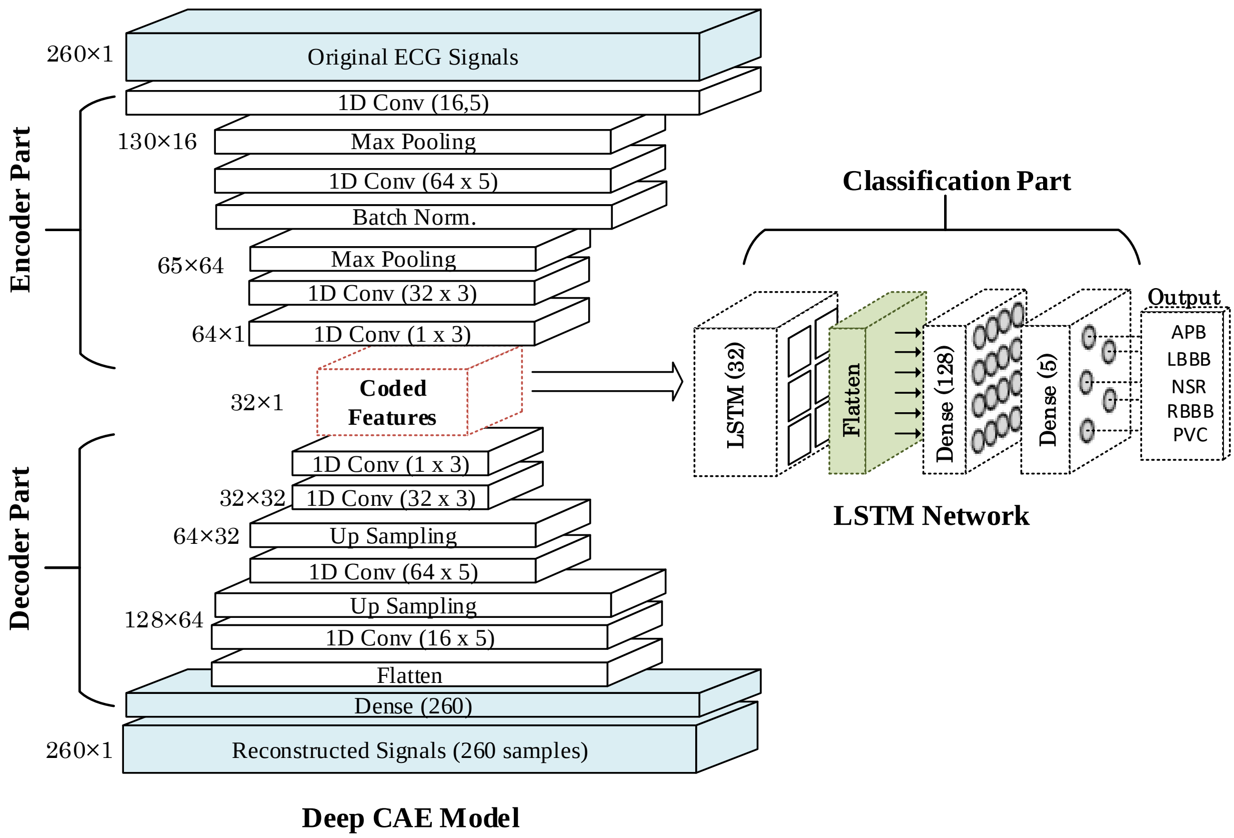


Figure 2. The block representation of the proposed deep CAE-LSTM recognition system.

Input signals are compressed with a 16-layer deep CAE model. The CAE model consists of two parts: encoder and decoder. In the encoder part, the original input signals are reduced to lower sized encoded features. Thus, large-sized input data is compressed and represented by small-sized data. The 1D convolutional layers in the encoder section constitute the feature maps, with a convolution operation used on the input data, and kernel parameters of the specified size. These feature maps are reduced by pooling layers, where the max pooling method was used in the study. In the max pooling method, designated areas are represented by a maximum value. Thereafter, a batch normalization layer was used on the encoder part to normalize the activations of the previous layer for each batch. As a result, encoded features of size 32 × 1 from the 260 × 1 sampled original input signals were obtained at the encoder portion of the system. For the decoder portion, it is possible to reconstruct the original signals by using encoded features. 1D convolution layers operate similarly to the encoder part. The Up-Sampling layers have an operation, opposite to the pooling layer in the encoder part, to achieve a data representation in higher dimensions. Therefore, the compressed data is expanded to a degree sufficient for representing the features which are similar in dimension to the original data. With the flatten layer in the decoder section, the data dimensions are converted to the appropriate size for the next dense layer. The flatten layer transforms a multidimensional vector into a one-dimensional vector; thus its usage is required between dense layers and convolutional layers. The last part of the decoding operation consists of the dense layer, in which compressed features were obtained from the original signal representations of the activation function. Table 2 presents the layer details and the parameters of the proposed CAE model.

Table 2. Layer details and parameters used for the proposed CAE ECG compression model.

	No	Layer Name	Kernel Size	Activation Function	Number of Parameters	Output Size
Encoder Part	**0**	Input	-	-	-	260×1
	1	Conv 1D	16×5	ReLU	96	260×16
	2	MaxPool 1D	2	-	-	130×16
	3	Conv 1D	64×5	ReLU	5184	130×64
	4	BatchNormalization	-	-	256	130×64
	5	MaxPool 1D	2	-	-	65×64
	6	Conv 1D	32×3	ReLU	6176	65×32
	7	Conv 1D	1×3	ReLU	97	65×1
	8	MaxPool 1D	2	-	-	32×1
Decoder Part	**9**	Conv 1D	1×3	ReLU	4	32×1
	10	Conv 1D	32×3	ReLU	128	32×32
	12	Up-Sampling	2	-	-	64×32
	13	Conv 1D	64×5	ReLU	10304	64×64
	14	Up-Sampling	2	-	-	128×64
	15	Conv 1D	16×5	ReLU	5136	128×16
	16	Flatten	-	-	-	2048
	17	Dense	260	Sigmoid	532740	260
	18	Output	-	-	-	260

These signals are presented as input to a deep LSTM network in order to implement the recognition process on the deep features encoded by the CAE method. The parameters of the LSTM network used for the classification process are given in Table 3.

Table 3. Layer details and parameters used for the LSTM based classifier model.

No	Layer Name	Unit Size	Other Layer Parameters
1	LSTM	32	Return Sequences=True
2	Flatten	-	-
3	Dense	128	Activation=ReLU
4	Dropout	-	Rate=0.1
5	Dense	2	Activation=Softmax

The LSTM network that was utilized for this study contains five layers. A 32-unit LSTM block was placed in the first layer of the network. A flatten layer was utilized to adjust LSTM output data and to make it suitable to interface with the dense layers following. After the flatten layer, a 128-unit dense layer was added. A dropout layer with 0.1 rates was used to prevent the overfitting problem from occurring. Then a five-unit dense layer was positioned as the last layer of the network, to automatically recognize the classes of ECG beat types. Therefore, the deep LSTM network classifies the types of arrhythmia from encoded features.

3.1 Convolutional Autoencoders (CAEs)

The Autoencoder is a special form of neural network (NN) which purposes to generate a copy of the input at its output [26]. Lower dimensional representations are kept in the hidden layers for the reconstruction of the input from the output [29]. Instead of these traditional internal neural network layers, Convolutional Autoencoders (CAEs) benefit from unsupervised learning of convolutional layers [30]. The convolutional part uses various number of layers with different kernel sizes as a filter to create an abstract information for the input [43]. CAEs differ from CNNs because they are not trained to solve a classification or a recognition problem. The training of these structures aims to decrease the loss ratio so that encoder and decoder parameters are updated during the training stage to minimize the reconstruction error. The reconstruction is a flip operation over the weights W with bias b and it is defined as follows.

$$R = \alpha\left(\sum_{i \in F} f_i * W_i + b\right) \tag{1}$$

In the equation, α denotes the activation function and the F denotes the set of the features. A CAE may have cascading convolutional operations similar to CNN models. The model is designed according to its reconstruction capability.

3.2 Long-Short Term Memory (LSTM)

LSTM is a special type of recurrent neural network (RNN) which contains memory blocks, memory cells and gate units [21, 23]. Gate units control the states of cells. For example, the input gate is responsible for the input flow to the memory cell for which the output gate conditionally operates to control the output stream. For the LSTM structure, the activation function is given in Eq.(2).

$$f_t = \alpha(W[x_t, h_{t-1}, C_{t-1}]) + b_f \tag{2}$$

In the equation x_t is given as the input sequence, W is weight vectors and b_f is the bias vector. For the LSTM memory blocks, h_{t-1} denotes the output of the previous block and C_{t-1} denotes the previous LSTM memory. The σ parameter represents the activation function. In the structure, it is possible to use different activation functions such as the logistic sigmoid function.

4. Experimental Results

The experimental results were examined under two categories: compression and classification. In the compression results, the obtained values and details of the experiments regarding the compression of beat signals by the CAE method are provided in the following section. The classification results included experimental findings for the recognition of both raw signals and coded signals with the deep LSTM network. The deep learning tool Keras [32], which is based on the Python programming language, was incorporated into the experimental component of the system. Tensorflow [33] was used as the back end of the Keras library. All experimental studies were performed on a computer having Intel Core i7-7700HQ 2.81GHz CPU, 16 GB memory and 8 GB NVIDIA GeForce GTX 1070 graphics card.

4.1 Compression Results

A deep convolutional autoencoder model was used to compress the ECG signals. The original ECG signals of 260 samples per segment were compressed into 32 sampled signals per segment. In experimental studies, it was observed that the performance of the CAE model decreased at too high compression ratios due to excessive lossy data, as well as when lower compression ratios (>32 samples per segment) were selected. Thus, the 32-sample compression structure has been selected, as this compression structure is the most suitable for the network structure. Compressed signals were then reconstructed, and metrics using evaluation criteria were obtained. Criteria that are widespread in the literature were used to evaluate reconstructed signal quality. These criteria are: a) Compression Ratio (CR), b) Root Means Squared (RMS), c) Percentage RMS Difference (PRD), d) PRD Normalized (PRDN), e) Quality-Score QS). Formulae related to these evaluation criteria are given in Table 4.

Table 4. Formulas for evaluation criteria which are used in the study.

Criteria	Equation	Criteria	Equation
PRD (%) :	$100.\left(\dfrac{\sum_{i=0}^{N-1}\left(X_o(i)-X_r(i)\right)^2}{\sum_{i=0}^{N-1}\left(X_o(i)\right)^2}\right)^{1/2}$	PRDN (%) :	$100.\left(\dfrac{\sum_{i=0}^{N-1}\left(X_o(i)-X_r(i)\right)^2}{\sum_{i=0}^{N-1}\left(X_o(i)-\overline{X}\right)^2}\right)^{1/2}$
RMS :	$\sqrt{\dfrac{\sum_{i=0}^{N-1}\left(X_o(i)-X_r(i)\right)^2}{N-1}}$	SNR :	$10.\log\left(\dfrac{\sum_{i=0}^{N-1}\left(X_o(i)-\overline{X}\right)^2}{\sum_{i=0}^{N-1}\left(X_o(i)-X_r(i)\right)^2}\right)$
CR :	$\dfrac{S_{or}}{S_{re}}$	QS :	$\dfrac{CR}{PRD}$

X_o: Original signal, X_r: Reconstructed signal, $\overline{X}$: Mean of signal, S_{or}: Size of original input, S_{re}: Size of reconstructed input.

From these criteria, CR gives the compression ratio, and it is obtained by dividing the area occupied by the original signal to the encoded signal size. The higher the CR value, the greater the degree of compression, and the more the amount of memory occupied by the signal decreases. For lossy data compression approaches, some components are lost when the original signal is reconstructed. The PRD ratio is an important parameter which provides a measure of the amount of data lost in the reconstructed signal. Consequently, the lower the PRD value, the lower the signal loss. The QS criterion determines the quality of the reconstructed signal. A high QS value indicates satisfactory compression quality. SNR, RMS, and PRDN are the other criteria which represent the amount of loss, and the presence of noise components in the compressed signal.

In this study, the deep CAE model used for the compression process on the 5-class arrhythmia data was first trained, and then the trained model was applied to test data. 70% of the data was used for model training, 50% of the remaining data was used in the validation process, and the other 50% was used in the test process. An Adam optimizer was used for optimizing the model during training. This optimizer had the following parameters. Learning rate (lr) = 0.001, beta1 = 0.9, beta2 = 0.999 and decay = $1E^{-5}$. The training phase was implemented for a total of 50 epochs, and the batch size was 128. The values of these parameters were adjusted with a brute force approach which was based on our previous studies on deep models over biomedical signals. For example, a value of 0.01 was initially determined for the lr and the performance of the model was observed when this parameter was gradually increasing or decreasing. Table 5 presents the compression results of the trained CAE model on the ECG data.

Table 5. Compression results of the trained CAE model on ECG data.

Class	**Number of Test Samples**	**Evaluation Criteria**				
		PRD (%)	**PRDN (%)**	**RMS (µV)**	**SNR (dB)**	**QS**
Atrial Premature Beat	384	0.64	15.06	0.003	39.00	12.50
Left Bundle Branch Block	1240	0.59	9.12	0.002	50.59	13.55
Normal	11250	0.61	11.05	0.002	46.34	13.11
Right Bundle Branch Block	1099	0.75	10.14	0.003	47.21	10.66
Premature Ventricular Contraction	1031	0.93	8.97	0.004	50.40	8.60
	Average	***0.70***	***10.86***	***0.002***	***46.70***	***11.68***

Since all of the used original ECG beats had a fixed dimension of 260, and the encoded features are 32-dimensional, the CR ratio has a fixed value of 8.125 for all data. As can be seen from the table, the average PRD ratio is 0.70 and the best PRD ratio is 0.59 for the LBBB class. In the compression stage, the PVC class had the most loss. The PRD ratio of the test signals in this class was observed to be 0.93. These results suggest that the proposed CAE model compresses the ECG beats of the arrhythmia data set with a good compression ratio. Figure 3 presents the scatter plot of the PRD evaluation criteria for each class. As is evident in the graph, the number of extreme data points is higher in the NSR class as compared with other classes. The main reason for this is that the amount of data in this class is quite high compared to other classes.

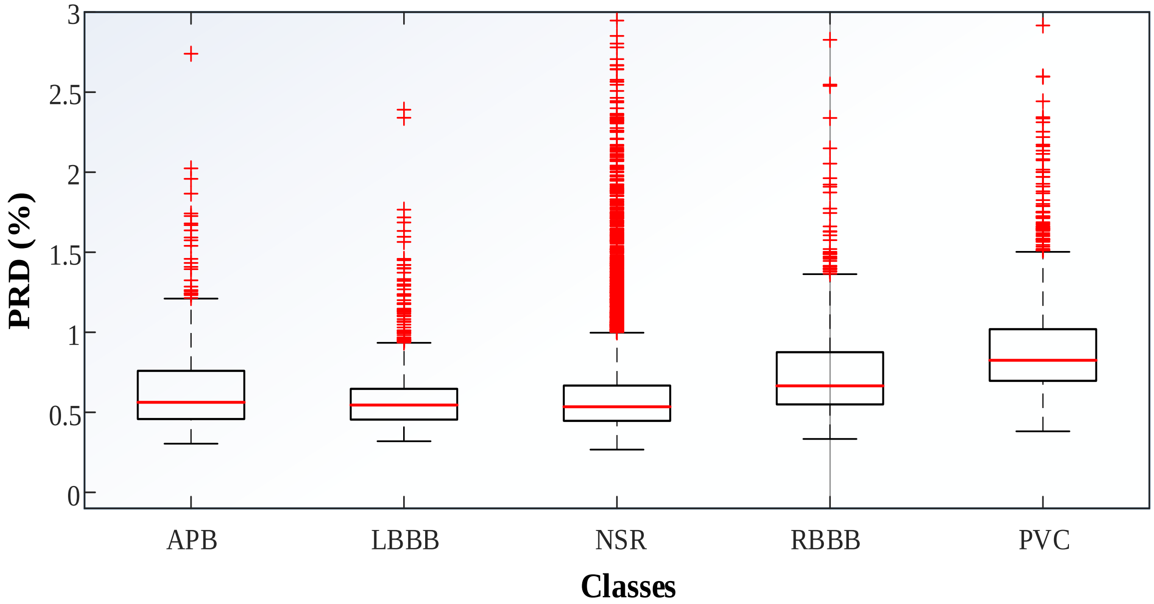


Figure 3. Bar plot of the PRD evaluation criteria for each class. The median line at the center of each box indicates the upper and lower limits of the box, respectively, at the 25th and 75th percentiles. The lines outside the box represent the most extreme data points, and the outliers are plotted individually using the red '+' symbol.

Figure 4 shows the waveforms of the original signal and reconstructed signal for a single sample from each class. It should be noted that the reconstruction process was realized with the deep CAE model. Both signals were superimposed to show the difference, which is assistive to analyze the effectiveness of the reconstruction process.

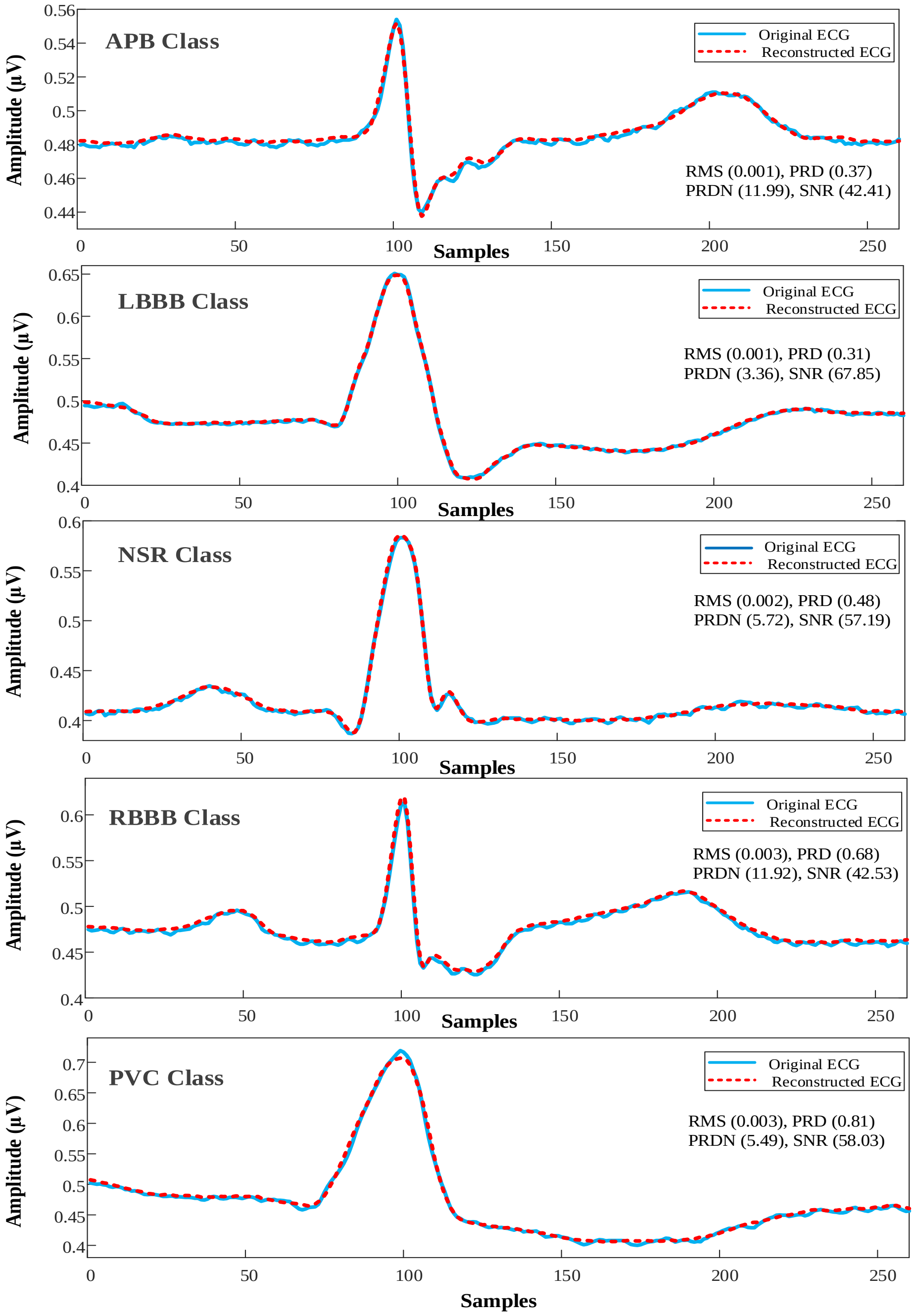


Figure 4. Example waveforms of the original signal and the deep CAE reconstructed signal, for a single sample of each class. The original ECG signals (blue trace) and reconstructed ECG signals (red trace) are plotted together, and overlap.

4.2 Deep Coded Features

In previous sections, it was described that the deep CAE model consists of two parts - encoder and decoder. The original input signals were converted into low-dimensional coded signals via the layers in the encoder section. Precisely, input ECG signals with 260 samples were represented by encoded signals with 32 samples at the output of the encoder layer. Moreover, the original input signal can be reconstructed from these coded signals. With the help of coded signals, long-term data storage of systems such as Holter can efficiently use their storage units. In addition, the proposed model offers a very advantageous structure, with both low size and secure data transfer to remote centers such as e-health systems. The model used in the encoder part provides the coding process with a non-linear structure, and it is necessary to have a decoder model trained in order to reconstruct these encoded signals to the original signal. In this respect, the proposed model ensures secure transmission of the ECG data. In this study, the use of coded signals was preferred for achieving two major aims. The first was to provide distinctive features in the classification stage, and the second was to shorten the time-consuming train and test durations of deep learning methods. Figure 5 shows the samples of ECG signals and their equivalent coded signals, which were obtained at the encoder stage.

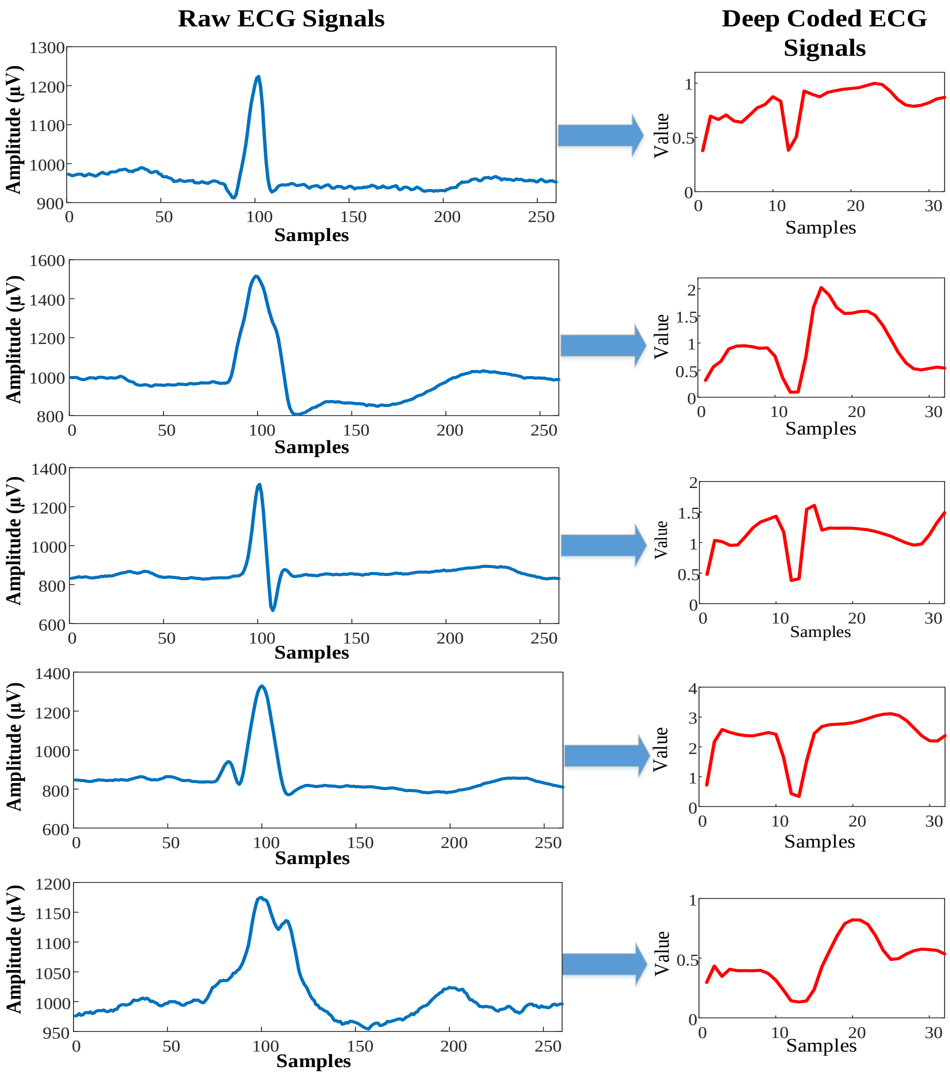
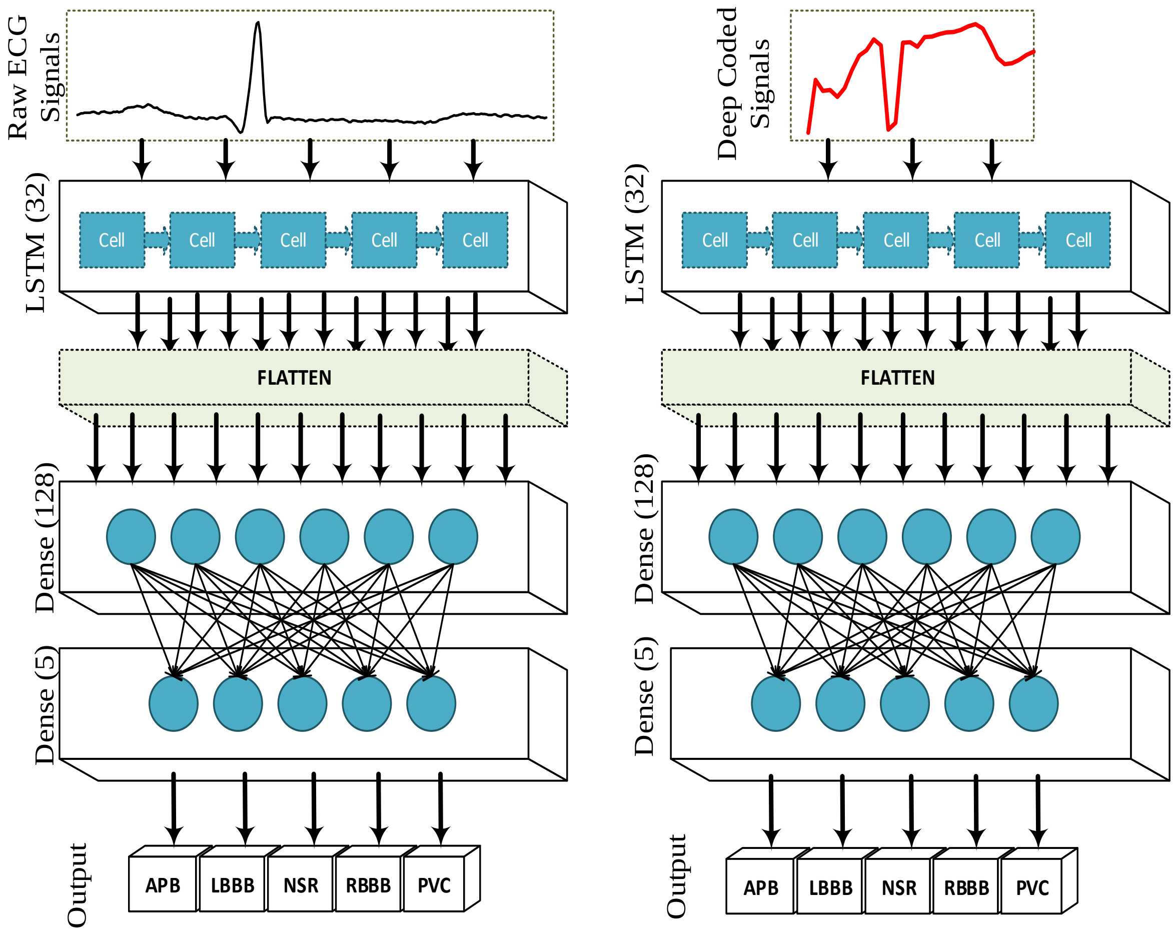


Figure 5. Samples of original ECG signals and their deeply coded signal representations.

4.3 Classification Results

Two different network structures were prepared for performance evaluation of the proposed classification system. In Figure 6 is depicted a block diagram of the network model, which is designed for the classification process. The only difference between these networks is in the input signals. The first deep LSTM network uses the original ECG signals with 260 samples as the input. The second network uses 32 samples of coded signals. The purpose was to evaluate the success of the convolutional autoencoder structure as both a compression device and as a feature extractor. During the training stage of the models, 70% of the ECG signals were used for training, 15% for validation, and the remaining 15% for test. The Adam optimizer was used with a batch size of 128. Categorical cross entropy was incorporated as the loss function of the networks.



a) Deep LSTM Network

b) Deep CAE-LSTM Network

Figure 6. Deep LSTM models designed for the classification stage. a) Deep LSTM network using raw ECG signals as input; b) Deep CAE-LSTM network using coded ECG signals as input.

The training stage of the designed networks was continued for 100 epochs, and the classification performance of the trained models was evaluated with the test data. Figure 7 shows the train and validation performances of the two networks during 100 epochs.

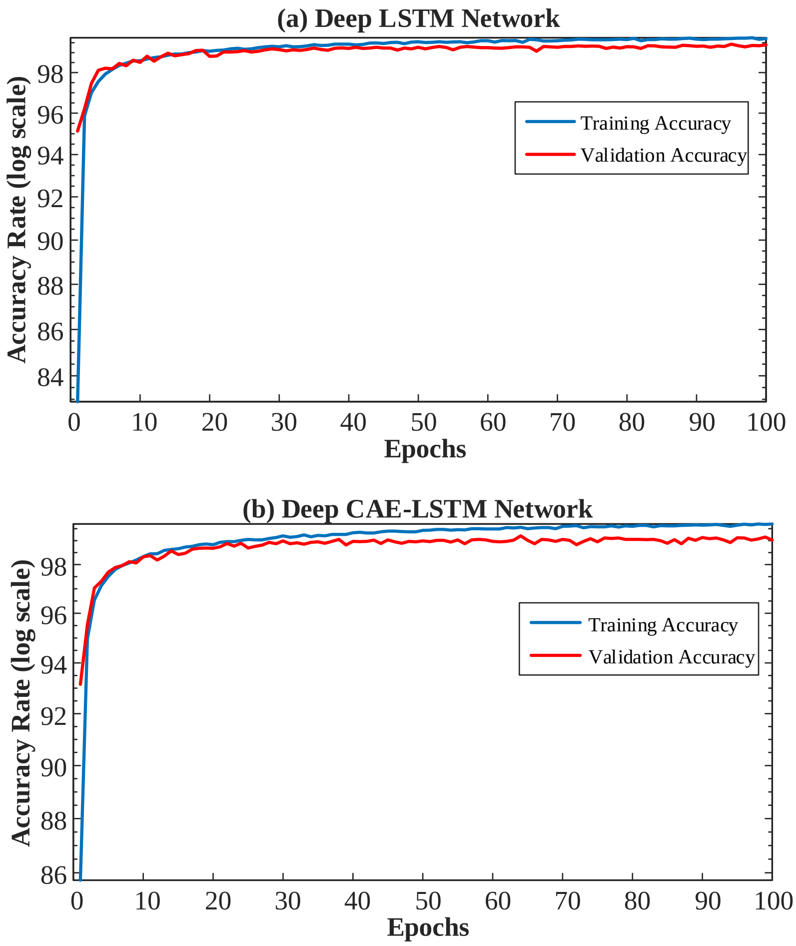


Figure 7. Train (blue lines) and validation (red lines) performance graphs of a) Deep LSTM network (at top) and b) Deep CAE-LSTM network (at bottom).

The performances of both networks used for classification were similar. The Deep LSTM network achieved a maximum 99.43% validation performance over a period of 100 epochs, while the CAE-LSTM network achieved a maximum of 99.21% validation for the same period. Neither network had an overfitting problem, and each demonstrated a high training performance. One of the most important performance criteria that distinguishes these networks has been the training time. Notably, one of the motivations of our study was the running time of networks during each epoch. When the LSTM network uses raw ECG signals with 260 samples as input data, the average computation time for each epoch was 165 seconds. Thus, the training stage required 16,500 seconds or approximately 4.5 hours for 100 epochs. On the other hand, each epoch of the CAE-LSTM network took an average of 22 sec when it received 32 encoded ECG signals as input. Therefore, the training stage of the CAE-LSTM network ran for 2,200 seconds or 0.61 hours. Although the training process is an offline process, models are trained in real-time in practice. However, the scenario is also important because it shows that the training on compressed data greatly reduces the computational time.

Test data, which is not used in training, are provided to the trained networks for the automatic recognition task. Some evaluation criteria such as accuracy, precision, recall and F1-score are employed to evaluate classification performances. Calculations of these criteria are given as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \tag{3}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5}$$

$$\text{F1-Score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall+Precision}} \tag{6}$$

For these equations, TP denotes the true positive, FP denotes the false positive, TN denotes the true negative and finally FN denotes the false negative. The classification performance on the 15,004 test data and evaluation criterion of the LSTM network, which used the raw data as input, is shown in Table 6.

Table 6. The evaluation criteria values of the Deep LSTM network with the test data.

Classes	Precision	Recall	F1-Score	Number of Data
APB	0.94	0.88	0.91	406
LBBB	1.00	0.99	1.00	1187
NSR	0.99	1.00	1.00	11199
RBBB	0.99	0.99	0.99	1101
PVC	0.99	0.98	0.98	1111
Avg/Total	**0.99**	**0.99**	**0.99**	**15004**

According to Table 6, the lowest performance was obtained in recognition of the APB class data. It is evident that the recognition performance of other classes is quite high. Average 99% and above values are measured for all evaluation criteria. In order to better understand the test results, the confusion matrix obtained for the 15,004 test data is given in Figure 8.

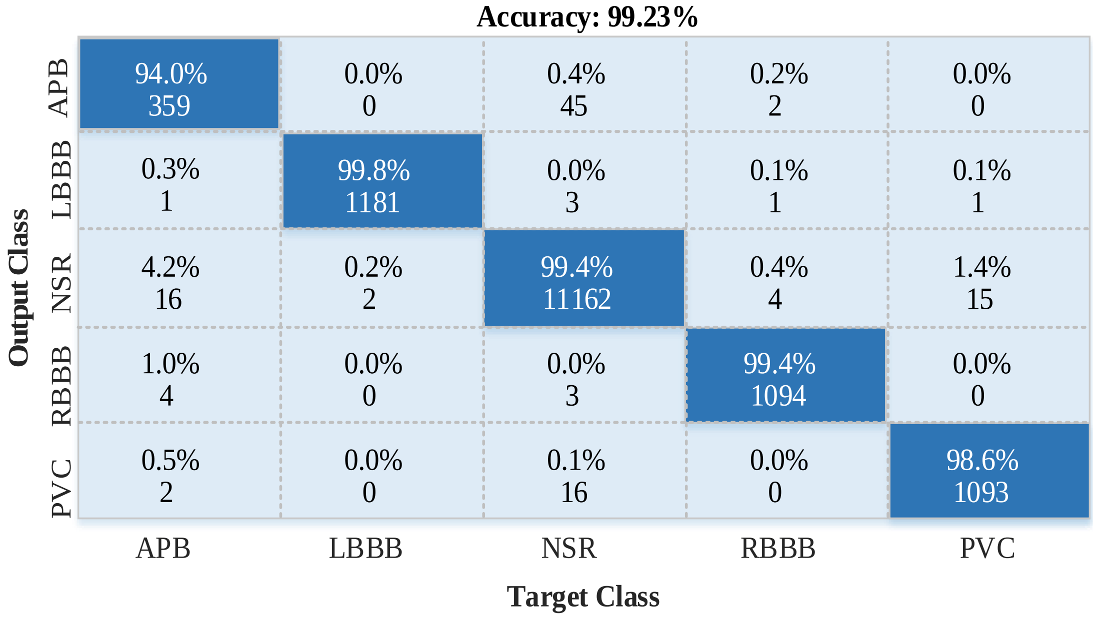


Figure 8. The confusion matrix obtained for the Deep LSTM network with the test data.

The deep LSTM network had an average accuracy of 99.23% on the 15,004 element test data. The LSTM network misclassified 45 APB data into the NSR class. Similarly, 16 NSR signals were included in the APB class, causing the lowest recognition performance between these two classes. Figure 9 shows some signal samples of the actual APB data which had been incorrectly classified as NSR. On the ECG, APB is an early atrial beat that is actually normally conducted through the atrioventricular node and subsequently the ventricle, similar to a NSR beat. The dominant surface ECG morphology, the QRS wave, represents ventricular electrical conduction. As such it is not surprising that APB and NSR bear similar QRS morphology, and may be confused. One distinguishing feature is the shortened time interval of the APB to the preceding beat, in contrast to the equal time intervals between NSR beats. Another important distinguishing feature is the presence of varying degrees of intraventricular conduction block in some but not all APBs (see Figure 9), depending on the electrical refractoriness of the ventricular conducting tissue, which is determined in part by the proximity of the APB to the preceding beat. Such time relationships are more suited for analysis by multi-beat algorithms such as in [18], but is outside the scope of the current study, which is based on beat-wise input and analysis.

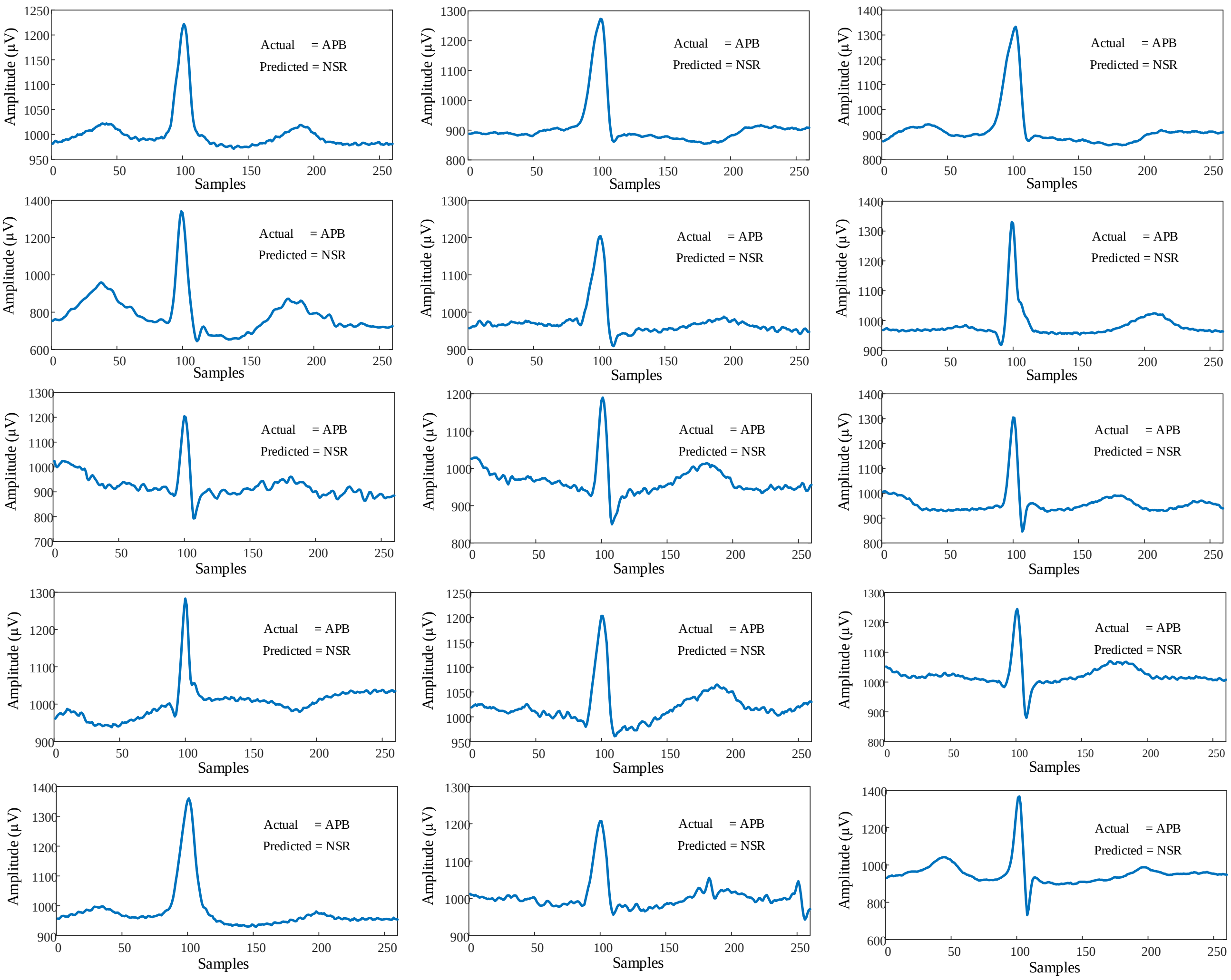


Figure 9. Some examples of APB beats which were mis-classified as NSR. Some of the beats appear slightly broad (second and third in first row; second in second row; first in last row) likely due to the presence of intraventricular conduction block (see text). Of note, time relationships to preceding beats are not apparent on the proposed beat-wise analytic approach.

When the processing time on the test data of the Deep LSTM network was measured, the test duration for a single sample was 0.05 sec. The average duration of the test for all samples was 28 sec. Table 7 presents the performance criteria values of the deep CAE-LSTM network, which was trained with the coded data.

Table 7. The evaluation criteria values of the Deep CAE-LSTM network with the test data.

Classes	Precision	Recall	F1-Score	Number of Data
APB	0.93	0.89	0.91	406
LBBB	0.99	0.99	0.99	1187
NSR	0.99	1.00	0.99	11199
RBBB	0.99	0.99	0.99	1101
PVC	0.98	0.98	0.98	1111
Avg/Total	**0.99**	**0.99**	**0.99**	**15004**

The results of Table 7 are similar to the deep LSTM test results, and it is again evident that data of APB class have the lowest evaluation criteria values. The confusion matrix obtained from the Deep CAE-LSTM approach is given in Figure 10.

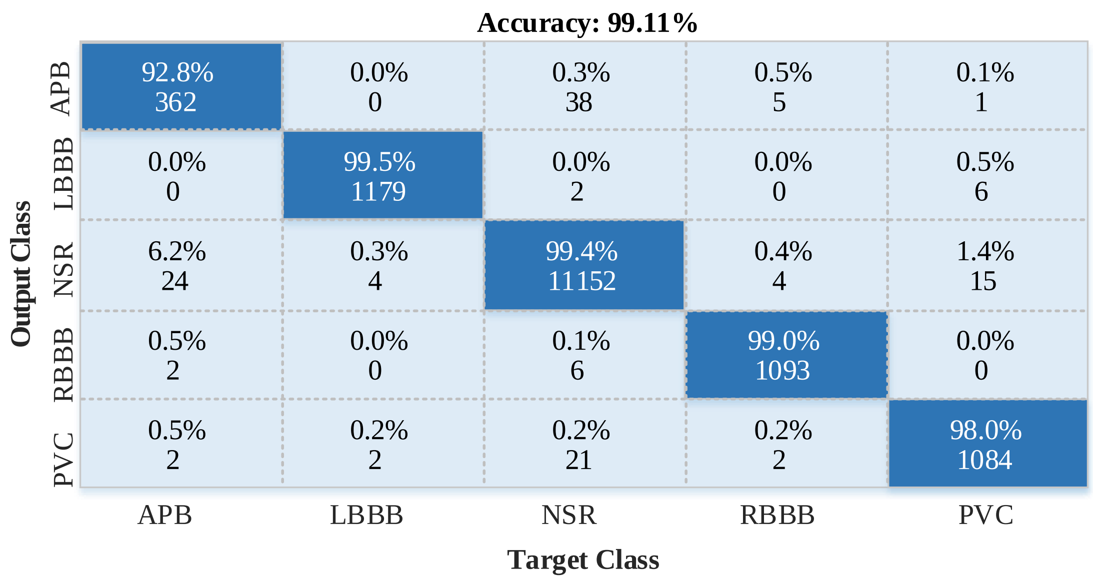


Figure 10. The confusion matrix obtained by the deep CAE-LSTM network on the test data.

The Deep CAE-LSTM network achieved an average performance of 99.11% on all data. The model misclassified 44 out of 406 observations in the APB class, but it achieved significant performances over the NSR, LBBB and RBBB classes. To compare the sample predictions for both networks, a calculation called false positive intersection rate (FPIR) was proposed for the overlap ratio of the CAE-LSTM network with the LSTM network.

$$FPIR_i(\%) = \frac{FP_i^1}{(FP_i^1 \cap FP_i^2)}.100 \tag{7}$$

Here, FP_i^1 and FP_i^2, respectively represent FP values of class *i* for the CAE-LSTM and LSTM networks. This calculation provides information on the extent to which the CAE-LSTM network has been misclassified in the LSTM network, as well as to the extent of the misclassified samples in class *i*. When confusion matrices for both networks were evaluated, the FPIR values for the classes were obtained as 67.3%, 25%, 15.66%, 86.48% and 62.29% for APB, LBBB, NSR, RBBB and PVC classes, respectively. The ratio of the same samples that both networks misclassified for the NSR class is lower than in the other classes. This is because the test data contains more examples for this class than the other classes.

The total time for classification of a single test data by the model was only 0.01 second. The total test duration for all samples was approximately 4 seconds. Table 8 presents performance comparisons for both deep LSTM and deep CAE-LSTM models in the training and testing stages.

Table 8. Performance comparisons of the LSTM and CAE-LSTM models on train and test data.

Models	**Time Cost**			**Classification Accuracy**	
	Training (100 epochs)	**Testing (All samples)**	**Coding (50 epochs)**	**Training**	**Testing**
LSTM	16500 sec (4.5 hours)	28 sec	-	99.43 %	99.23 %
CAE-LSTM	2200 sec (0.61 hours)	4 sec	920 sec	99.21 %	99.11 %

According to Table 8, both models provide a recognition performance of more than 99% for test data. The training, validation and testing performance of the CAE-LSTM model was slightly lower than the LSTM model which was tested with the original signals. The main reason for this is that the compression technique used in the study is a lossy compression and some features are lost during the compression. However, the minute difference is unlikely to be clinically significant. Considering the performance of the proposed method, we could state that the number of missing features is few and the proposed classifier is robust, even when working with the lossy data.

The most significant difference between the two models is the total time requirement for training and testing stages. The training stage of the Deep LSTM model was approximately 4.5

hours in duration, while the CAE-LSTM, which uses coded features, lasted only about 0.5 hours. In other words, the CAE-LSTM model is approximately seven times faster than the deep LSTM model. In addition, the CAE-LSTM model spent about 50 epochs (approximately 920 sec) as an extra time when coding the samples in the CAE section.

5. Discussion

Many studies have been conducted in the literature to identify ECG signals on the MIT-BIH arrhythmia database. Table 9 provides a brief summary of some of these studies. Martis et al. [34] have achieved a 98.11% performance for classification of five types of cardiac class by using Principal Component Analysis (PCA) feature sets and the least-squares support vector machine (LS-SVM) classifier. Elhaj et al. [35] achieved a success of 98.91% using a combination of linear PCA-discrete wavelet transform (DWT) and nonlinear HOS-independent component analysis (ICA) extraction techniques for arrhythmia detection and recognition. In their study, Yang et al. [36] reported a 97.94% accuracy for classification of five types by using the PCA network (PCANet) feature extraction with a linear SVM. Li and Zhou [46] have used wavelet packet entropy (WPE) based features and random forest (RF) to classify input ECG signals.

In most of the deep learning studies, raw ECG signals, which often include a preprocessing unit, are used. Kiranyaz et al. [14] proposed a CNN-based patient-specific ECG heartbeat classifier. They reported 99.00% performance with a classifier that uses raw signals as input. Zubair et al. [37] used the CNN model for ECG beat classification and they obtained a recognition rate of 92.70%. Yang et al. [47] have presented a stacked sparse auto-encoders (SSAEs) based classification method for recognition of six types of ECG beats. Acharya et al. [39] proposed a deep learning based arrhythmia classification model. In their study, one dimensional CNN model was applied for 5 class ECG signals, and this method showed 94.03% accuracy. Yildirim [23] proposed the use of LSTMs for this research area, where DWT sub-bands of ECG signals were used in sequence to increase the performance of the LSTM. Oh et al. [2] achieved 98.10% performance using the CNN-LSTM in variable length ECG beats. Sellami et al. [48] have presented a deep CNN model that contains 9 convolution layers for classification of heart beats. They have obtained a 99.48% accuracy rate under an intra-patient paradigm and 88.34% under an inter-patient paradigm. Another noteworthy deep learning study is the CNN model for long duration ECG signals, which was presented by Yildirim et al. [19].

In the study, automatic recognition of ECG signals with 17 class sizes of 3,600 (10 s) was achieved with 91.33% accuracy.

Table 9. Comparison of selected recognition studies on the MIT-BIH data set with the proposed approach.

Study	Number of Classes	Feature Set	Classifier	Signal Length	Accuracy (%)
Martis et al., 2012 [34]	5	ECG+PCA	LS SVM	200 samples (0.56 s)	98.11
Elhaj et al., 2016 [35]	5	(PCA-DWT)+ (ICA-HOS)	SVM	200 samples (0.56 s)	98.91
Yang et al., 2018 [36]	5	PCANet	Linear SVM	300 samples (0.83 s)	97.94
Li and Zhou, 2016 [46]	5	WPE+RR	RF	143 samples (0.39 s)	94.61
Kiranyaz et al., 2016 [14]	5	Raw data	CNN	64 and 128 samples	99.00
Zubair et al., 2016 [37]	5	Raw data	CNN	200 samples (0.56 s)	92.70
Yang et al., 2016 [47]	6	SSAEs	Softmax	250 samples (0.69 s)	99.50
Acharya et al., 2017 [39]	5	Raw data	CNN	360 Samples (1 s)	94.03
Yildirim, 2018 [23]	5	DWT sub bands	BLSTM	360 samples (1s)	99.39
Oh et al, 2018 [2]	5	Raw data	CNN+LSTM	Variable	98.10
Sellami et al., 2019 [48]	5	Raw data	CNN	170 samples (0.47 s)	99.48
Yildirim et al. 2018 [19]	17	Raw data	CNN	3600 samples (10s)	91.33
The proposed	**5**	**Raw data**	**LSTM**	**260 samples (0.72 s)**	**99.23**
	5	**Coded Features**	**LSTM**	**260 samples (0.72 s)**	**99.11**

Our study (marked in bold, Table 9), differs from other studies in the literature in that both the compression and classification components were performed on ECG data by using deep learning methodologies. The deep CAE approach has been proposed for compression of various signals. To the best of our knowledge, this is the first study that uses CAE to compress ECG arrhythmias according to their classes. The LSTM network was implemented for the classification of arrhythmias. There are other studies in the literature which have classified ECG signals by using LSTM networks [2, 23]. The main difference is that our study used compressed coded features of ECG signals to reduce the time cost of the LSTM networks. As a result, the time costs of the classifier during the training and testing phase have been significantly reduced. In our previous work [23], we used DWT sub-bands to generate multiple features for LSTM networks. This approach improved classification performance of LSTM. Unlike our previous study, in this paper we focused on both classification and compression performances. Also, we have used a dataset that contains a higher number of beats than in our previous study [23]. In this dataset, segments were created to include 99 samples prior to the R peak, and 160 samples following the R peak. Thus each beat has 260 samples.

The advantages of this study can be summarized as follows:

- ECG signals are compressed according to the types of arrhythmia, so that data size was reduced. This operation was performed with low loss compression.
- This approach may significantly reduce the cost of hardware for diagnostic systems, such as mobile health, Holter, and tele-medicine. These systems require continuous and remote monitoring of ECG data.
- The model provides an appropriate coding structure for the secure transmission of patient data.
- With the help of the coded features, the model reduces the training time, which is challenging for most deep learning models.
- LSTM and CAE-LSTM models can classify arrhythmia types with very high recognition ratios.

The main disadvantages of this study can be defined as follows:

- It requires a complex deep learning model for compression.
- Processes on raw data, which are required to obtain coded features, take additional time.

In future studies, the model will be analyzed for long duration arrhythmia types. The performance of the model will be measured with this long duration data. In addition, the proposed approach will be examined for other types of arrhythmias. In this study, the performance of our method was reported based on a per ECG segment analysis. Performance evaluation of the model on a per patient basis will be a part of future studies. Also, we will try to use these coded features with some traditional classifiers, such as SVM, Random Forests and multi-layer perceptron. Thus, comprehensive assessments will be included in future studies.

6. Conclusion

In this study, a coded feature-based deep LSTM network model has been proposed to recognize ECG arrhythmia signals. Two important research problems for automatic ECG signal recognition are discussed. The first is to reduce the data size for minimizing the storage requirement and data transfer costs. This will be beneficial for popular applications such as e-health and mobile health applications. Moreover, it was ensured that the health data was securely transferred to remote locations as compressed by a non-linear model. For this purpose, a deep CAE based compression model was designed. The Deep CAE model compressed signals in each class with a significantly low loss rate of 0.70 PRD and 11.68 QS. The second was the automatic recognition of beat signals. For this purpose, LSTM networks, which have recently come into prominence in the processing of sequential data, have been used. In this study, two LSTM networks were prepared for the use of the original and coded ECG beats as input data. Data recognition performance of these networks was 99.23% and 99.11%, respectively. One of the most significant contributions of the study was in the reduction in training time of the deep LSTM network with coded signals from 4.5 hours to 0.6 hours.

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