Arrhythmia Detection Using Deep Convolutional Neural Network With Long Duration ECG Signals

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Arrhythmia detection using deep convolutional neural network with long duration ECG signals

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ABSTRACT

This article presents a new deep learning approach for cardiac arrhythmia (17 classes) detection based on long-duration electrocardiography (ECG) signal analysis. Cardiovascular disease prevention is one of the most important tasks of any health care system as about 50 million people are at risk of heart disease in the world. Although automatic analysis of ECG signal is very popular, current methods are not satisfactory. The goal of our research was to design a new method based on deep learning to efficiently and quickly classify cardiac arrhythmias. Described research are based on 1000 ECG signal fragments from the MIT - BIH Arrhythmia database for one lead (MLII) from 45 persons. Approach based on the analysis of 10-s ECG signal fragments (not a single QRS complex) is applied (on average, 13 times less classifications/analysis). A complete end-to-end structure was designed instead of the hand-crafted feature extraction and selection used in traditional methods. Our main contribution is to design a new 1D-Convolutional Neural Network model (1D-CNN). The proposed method is 1) efficient, 2) fast (real-time classification) 3) non-complex and 4) simple to use (combined feature extraction and selection, and classification in one stage). Deep 1D-CNN achieved a recognition overall accuracy of 17 cardiac arrhythmia disorders (classes) at a level of 91.33% and classification time per single sample of 0.015 s. Compared to the current research, our results are one of the best results to date, and our solution can be implemented in mobile devices and cloud computing.

1. Introduction

Electrocardiography (ECG) is the most basic and accessible method of diagnosing cardiac arrhythmia (or heart rhythm disorders), as it is a non-invasive and easy to use method that can provide useful information on heart health and pathology. Cardiac arrhythmia is an important manifestation of cardiovascular disease. The latter is a serious societal problem due to 1) its high prevalence and incidence, 2) associated high mortality (every year, 17.3 million persons die from cardiovascular disease, accounting for 37% of all deaths globally [66–68]), and 3) resultant high cost of treatment (the usual chronic course of the disease necessitates long-term and frequently expensive therapies [69,70]). The above issues will intensify with the expected progressive aging of populations worldwide and hence may increase number of deaths from 17 million in 2016 to 24 million in 2030 [66–68,71]).

Existing algorithms for automated ECG recognition of cardiac arrhythmia are based on the assessment of morphological features of single or few QRS complexes or beats. In the scientific literature, analysis of QRS complexes is substantially more popular than the analysis of long-duration ECG signal fragments [45]. Current methods can be error-prone and may not achieve satisfactory diagnostic performance due to high beat-to-beat variability of these features among individuals [29,43]. This motivated us to conduct research on a new solution of diagnosing heart disease using long-duration continuous ECG beat signals, which we hypothesise as more accurate than conventional algorithms. An important design consideration is our intention to reduce the computational complexity of our developed algorithms, so as to facilitate implementation of our solution in mobile devices and cloud computing to monitor patients' health in real time.

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Deep learning [4,7,8,10,16,26,54] is a type of machine learning technique that is characterized by a hierarchical architecture comprising multiple layers in which subsequent stages of information processing take place. The input layers are used to extract features, based on which the output layers perform the analysis and classification of patterns. Deep learning methods can be divided into various subtypes based on the training methods: (i) deep discriminatory models, e.g. deep neural networks (DNNs) [54], recurrent neural networks (RNNs) [15] and convolutional neural networks (CNNs) [26]; and (ii) unsupervised/generative models, e.g. restricted Boltzmann machines (RBMs) [17], deep belief networks (DBNs) [10], deep Boltzmann machines (DBMs) [51] and regularized autoencoders [7].

CNNs are most often used for processing two-dimensional data, including images [16,80,81,87]. CNN consists of at least one hidden (convolutional) layer completely connected to the upper layer (same as in typical neural networks) and also contains weights. The hidden layers of a CNN typically consist of convolutional layers, pooling layers, fully connected layers and normalization layers. The CNN network architecture is suitable for the processing of 2D data. Compared to other deep learning architectures, CNN achieves better results for image processing and speech recognition [80,82,85,87]. CNN networks can be trained by a standard error backpropagation algorithm. It is easier to train than other regular, deep, unidirectional neural networks because CNN has much less parameters to optimize, which makes this architecture very attractive to use.

Deep learning has become very popular recently [13,84], and has been applied successfully for the classification of heart disease and arrhythmia using CNN [1,2,23,88,89] DNN [48], long-short term memory network (LSTM) [47,62,72,90].

2. Related works

The ECG signal, although simple to acquire, contains rich features that can be mined for computational analysis. Its potential and popularity for research are reflected in the growing numbers of publications in subjects concerning ECG: (i) classification or detection of ECG beat [5,32,33,56,63]; (ii) deep learning [3,23,48]; (iii) principal component analysis [12,21,22,32,34,35,49,58]; (iv) higher order statistics [36–38]; (v) feature selection/dimensionality reduction [11,24,28,31,39,61,64,65]; (vi) noise [27,44,50]; (vii) discrete wavelet transform [9,12,19,25,32,41,57,60]; (viii) independent component analysis [12,32,53]; and (ix) ensemble learning [18,20,40,46,52].

The main goals of the research were to design:

- A new, efficient and fast 1D version of CNN model (1D-CNN) for the automatic classification of cardiac arrhythmia based on 10-second (s) fragments of ECG signals;
- Methods with low computational complexity that can be used on mobile devices and cloud computing for tele-medicine, e.g. patient self-monitoring and preventive health.

In our study, a new non-complex 1D-CNN has been developed that recognizes the 10-s ECG signal fragments. 10s is the typical duration of the rhythm strip acquisition on a routine 12 lead ECG. This is expedient, as the algorithm can then be applied without alteration. To the authors' best knowledge, no prior research in the literature (outside of articles [45,46]), has focused on the analysis of 10-s fragments of ECG signal. If successful, our research may significantly enhance the accuracy of ECG analysis at reduced computational costs. The CNN can be used generally for the classification of other time-series data, which can garner widespread application. Novel elements of our research, based on a literature review [6,29,30], include:

- New machine learning method based on an optimal structure of 1D version of CNN;
- New methodology based on the analysis of long duration (10-s) signals of ECG that contain many heart evolutions; and
- Recognition of 17 classes of cardiac arrhythmia.

3. Material and methods

In this study, CNNs were used to classify long-duration fragments of ECG signal (10-s). The designed classifier system has a complete end-to-end structure with neither hand-crafted feature extraction of the signals nor feature selection at any stage [16,80,86,87]. For this purpose, a 16-layer deep network structure including standard CNN layers was designed. The input of this network structure comprised 3600 samples of long-duration raw ECG signals. At the classifier network output, prediction of the classes to which the signals belong had been provided. Unlike standard techniques, no QRS detection and segmentation was performed on the ECG signals. Comprehensive performance evaluations of the network were made on the ECG database containing 1000

Table 1
The number of ECG signal fragments used for the various ECG classes.

No	Class	Fragment Numbers	Number of Used Fragments								
			13-classes			15- classes			17- classes		
			Train	Val	Test	Train	Val	Test	Train	Val	Test
1	Normal sinus rhythm	283	198	44	41	200	51	32	200	47	36
2	Atrial premature beat	66	46	14	6	45	11	10	44	10	12
3	Atrial flutter	20	14	1	5	13	3	4	13	3	4
4	Atrial fibrillation	135	95	23	17	94	21	20	96	21	18
5	Supraventricular tachyarrhythmia	13	–	–	–	–	–	–	9	2	2
6	Pre-excitation (WPW)	21	15	4	2	14	3	4	15	4	2
7	Premature ventricular contraction	133	–	–	–	94	21	18	98	19	16
8	Ventricular bigeminy	55	39	6	10	38	7	10	38	8	9
9	Ventricular trigeminy	13	10	2	1	10	2	1	10	2	1
10	Ventricular tachycardia	10	–	–	–	7	1	2	7	1	2
11	Idioventricular rhythm	10	6	1	3	7	2	1	7	2	1
12	Ventricular flutter	10	6	2	2	6	1	3	6	1	3
13	Fusion of ventricular and normal beat	11	–	–	–	–	–	–	7	3	1
14	Left bundle branch block beat	103	73	12	18	73	13	17	73	11	19
15	Right bundle branch block beat	62	43	8	11	43	4	15	45	8	9
16	Second-degree heart block	10	7	2	1	6	2	2	6	3	1
17	Pacemaker rhythm	45	31	6	8	30	7	8	26	4	14
	Total	1000	583	125	125	680	149	147	700	150	150

[*Test: Testing; Train: Training; Val: Validation].

Table 2
Detailed parameters used for all the layers of proposed 1D-CNN model.

Layer	Layer Name	Kernel × Unit	Other Layer Parameters
1	Conv1D	50 × 128	Activation = ReLU, Strides = 3
2	Batch Norm.	–	–
3	MaxPooling1D	–	Pooling Size = 2, Strides = 3
4	Conv1D	7 × 32	ReLU, Strides = 1
5	Batch Norm.	–	–
6	MaxPooling1D	–	Pooling Size = 2, Strides = 2
7	Conv1D	10 × 32	ReLU, Strides = 1
8	Conv1D	5 × 128	ReLU, Strides = 2
9	MaxPooling1D	–	Pooling Size = 2, Strides = 2
10	Conv1D	15 × 256	ReLU, Strides = 1
11	MaxPooling1D	–	Pooling Size = 2, Strides = 2
12	Conv1D	5 × 512	ReLU, Strides = 1
13	Conv1D	3 × 128	ReLU, Strides = 1
14	Flatten	–	–
15	Dense	1 × 512	ReLU, Droput Rate = 0.1
16	Dense	1 × {13,15,17}	Softmax

fragments. In experimental studies, results were obtained on different cases using 13-, 15- and 17-classes.

3.1. Assumptions

The described research was based on published methodology [45,46]. The main features of the new methodology were:

- Analysis of 10-s fragments of ECG signal (as opposed to single QRS complexes);
- No signal filtering;
- No QRS complexes detection and segmentation;
- End-to-end structure in which classification and feature extraction and selection stages were combined; and
- Analysis of ECG signal fragments that each contain one unique class type (other than normal sinus rhythm).

Table 3
Detailed classification performance for various number of classes using our proposed model.

Classes	SEN (%)	SPE (%)	Precision (%)	Recall (%)	F-Score (%)	Overall AC (%)
13-Classes	93.52	99.61	92.52	93.52	92.45	95.2
15-Classes	88.57	99.39	90.48	88.57	89.28	92.51
17-Classes	83.91	99.41	89.52	83.91	85.38	91.33

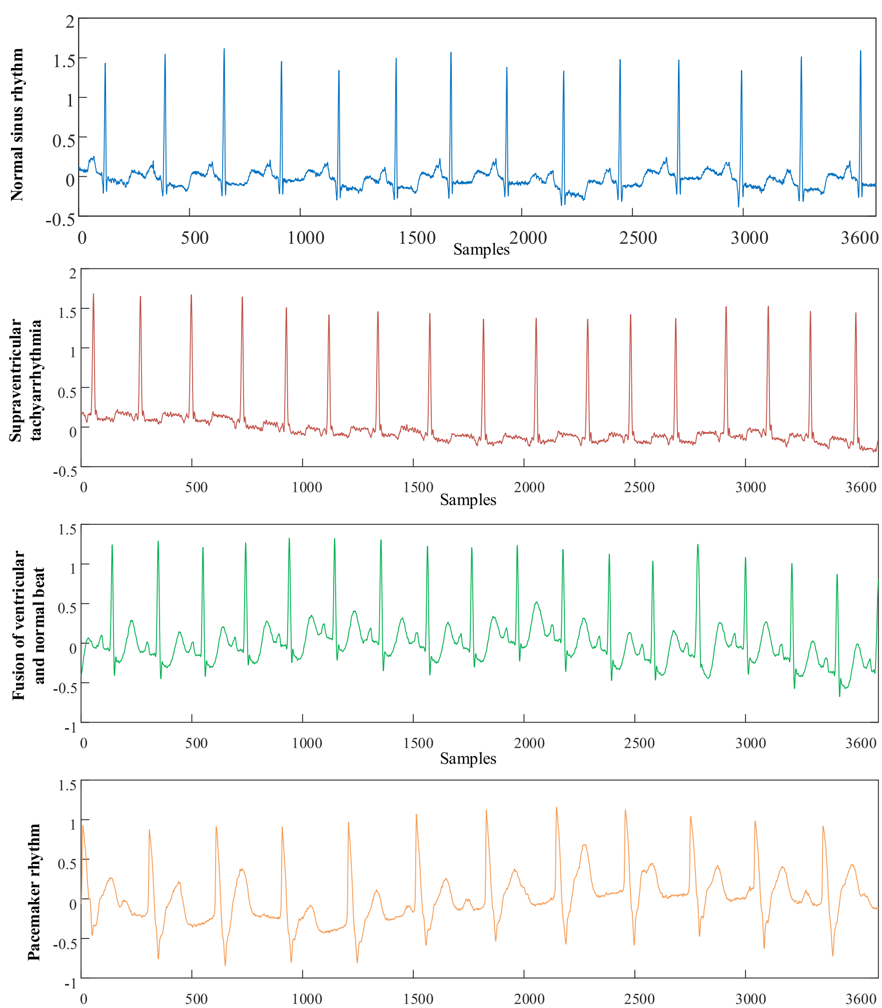

Fig. 1. Typical signal samples of different classes.

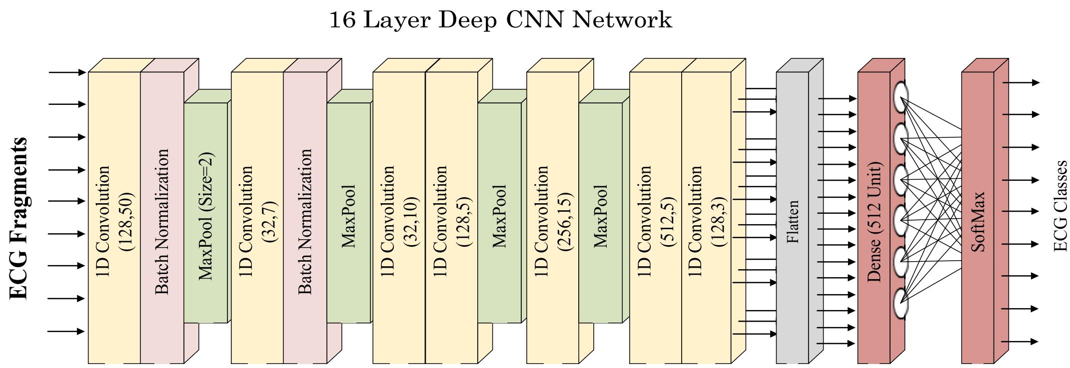

Fig. 2. Block diagram of the proposed 16 layer CNN model.

In Ref. [45] single machine learning methods and in Ref. [46] ensemble of classifiers were employed. In our proposed method novel CNN model for long-duration of ECG signal fragments is used.

3.2. ECG database

From the MIT-BIH Arrhythmia database [42], hosted at PhysioNet (http://www.physionet.org) [14], ECG signals were acquired. The research ECG dataset comprised 3600 10-s non-overlapping samples extracted from 1000 randomly-selected ECG signal fragments that had been recorded at sampling frequency of 360 Hz and gain of 200 adu/mV at a single ECG lead position (MLII) among 45 individuals: 19 females (age range 23–89 years) and 26 males (age range 32–89 years). Seventeen unique diagnostic classes (normal sinus rhythm, pacemaker rhythm, and 15 types of cardiac arrhythmia) were represented in Table 1.

Table 1 tabulates the various cardiac arrhythmia diagnostic classes, the associated number of ECG signal fragments collected, and their distributions into training, validation and test sets. It was not possible to obtain more suitable ECG signal fragments for the least common of the

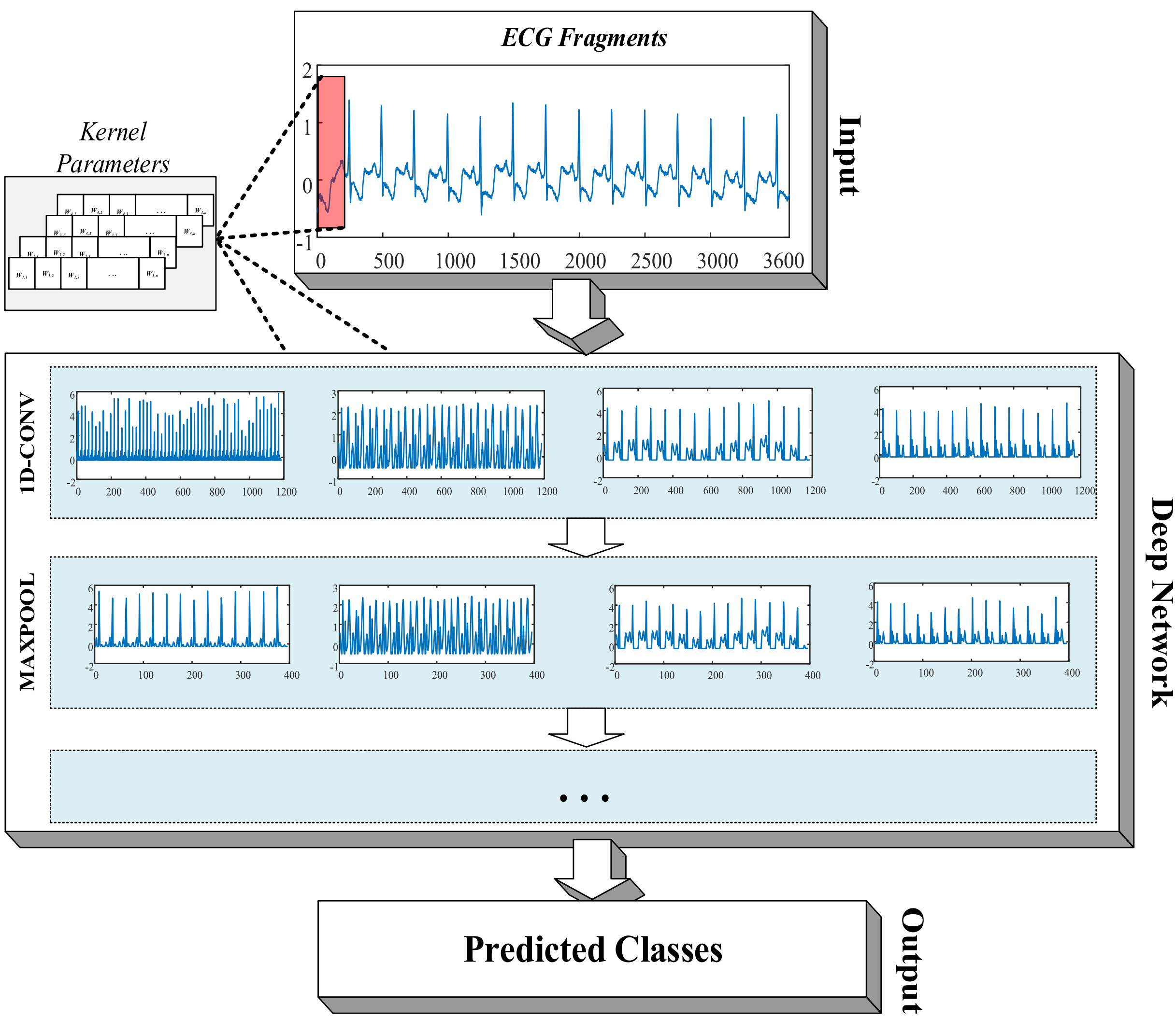

Fig. 3. Illustration of 1D convolution and max pooling processes on the ECG fragment signals.

specified diagnostic classes (rows 10 and 13 in Table 1) from the MIT-BIH Arrhythmia database, which necessitated sensitivity analysis using smaller number of diagnostic classes (see Results section below and Table 3). Fig. 1 shows the typical ECG signals obtained from the ECG dataset.

3.3. Methods

3.3.1. Preprocessing with normalization

Constant component reduction and gain reduction were applied, and three types of normalization were tested: (i) no normalization; (ii) signal rescaling to the range [-1,1] and constant component reduction; and (iii) signal standardization (standard deviation of signal = 1 and mean value of signal = 0). Finally, rescaling was implemented for which the best results were obtained.

3.3.2. Proposed 1D-CNN classification model

A 16-layer deep convolutional network was designed for the classification of ECG signals according to cardiac arrhythmia. This deep network model provides automatic classification of input fragments through an end-to-end structure without the need for any hand-crafted feature extraction or selection steps [7,16,80,81,86]. The structure of the deep network model consists of the classical CNN layers, but the structure of 1D-CNN is predominant. In 1D convolution layers, feature maps that are representations of ECG fragments are subjected to convolution processing with weights of various sizes. The 16-layer deep 1D-CNN model designed in the study is shown in Fig. 2.

In the first layer of the model, 1D convolution is performed with 128 wt vectors on the input ECG signals. The activation outputs of this layer are normalized using batch normalization layer for each batch. In the 1D max pooling layer, new feature maps are generated by taking the maximum values in the region specified on the feature maps obtained from the previous layers. This layer reduces the size of feature maps from the previous layer according to the region size. The reducing feature map sizes is an important step in reducing the computational cost of deep learning structures. For this purpose, different methods such as average values are used instead of maximum values in 1D Max layer.

In the fourth layer, the convolution process is repeated on the input feature maps with 32 × 7-size weights. By performing batch normalization process again, the feature maps whose region width is set to two are reduced by half using pooling method on the 6th layer. These operations are repeated in the next 1D convolution and 1D max pooling layers. An illustrative representation of the successive convolution and pooling operations using ECG signals is given in Fig. 3.

The proposed deep network has a flattened layer on the 14th layer so that the feature maps obtained from the 13th layer can be transformed to the appropriate size as an input to the subsequent layers of the network. This layer transforms multidimensional input feature vectors into one-dimensional output data. The features obtained from the flattened layer are fed to a dense-connected neural network layer of 512 units. In the last layer of the network, there is a layer of softmax which is the unit of the number of the output classes. Using the softmax layer, the prediction of the class to which the input data belongs is realized. In addition to all of these, some layers have a dropout parameter to prevent the overfitting during the learning phase. After developing the model, the layer numbers, types and parameters of the deep algorithm are changed by brute force technique and the performances of the validation sets are observed. Our devloped 16-layer model, yielded the highest classification results for long duration ECG

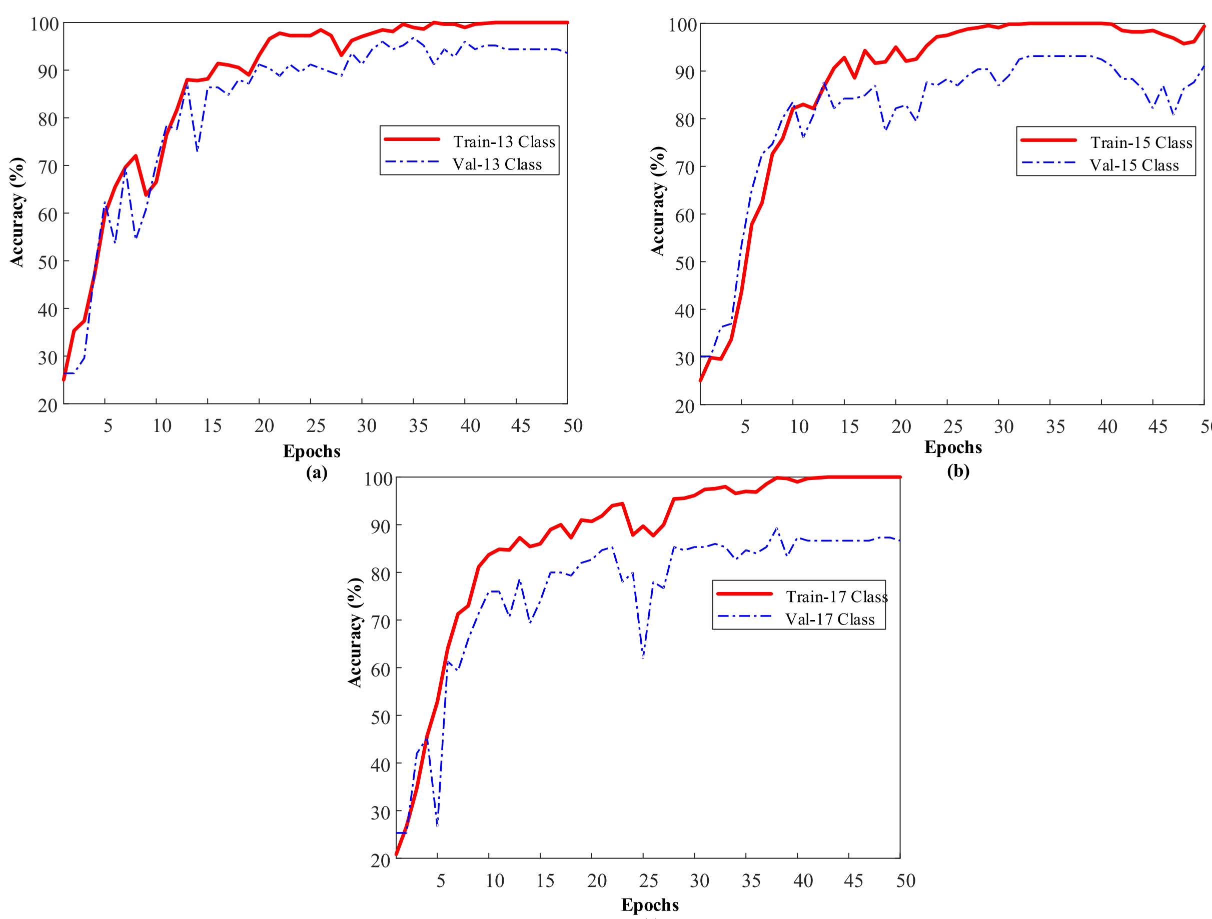

Fig. 4. Training and validation performances using our proposed model with ECG datasets: (a) 13-classes, (b) 15-classes, c) 17-classes.

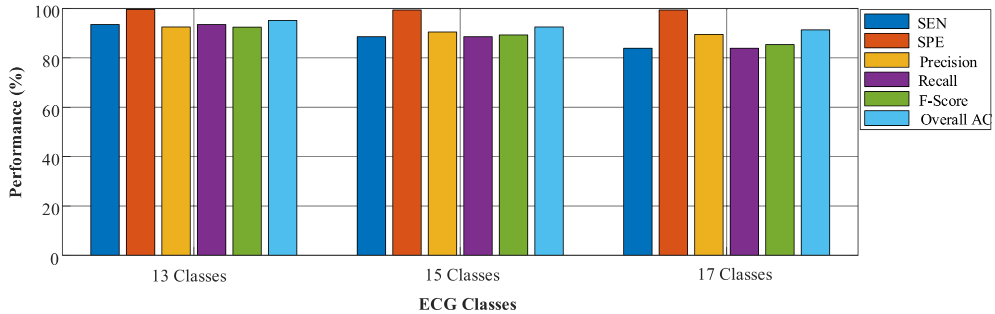

Fig. 5. Graphical representation of classification performances for different number (13,15 and 17) of classes using the proposed model.

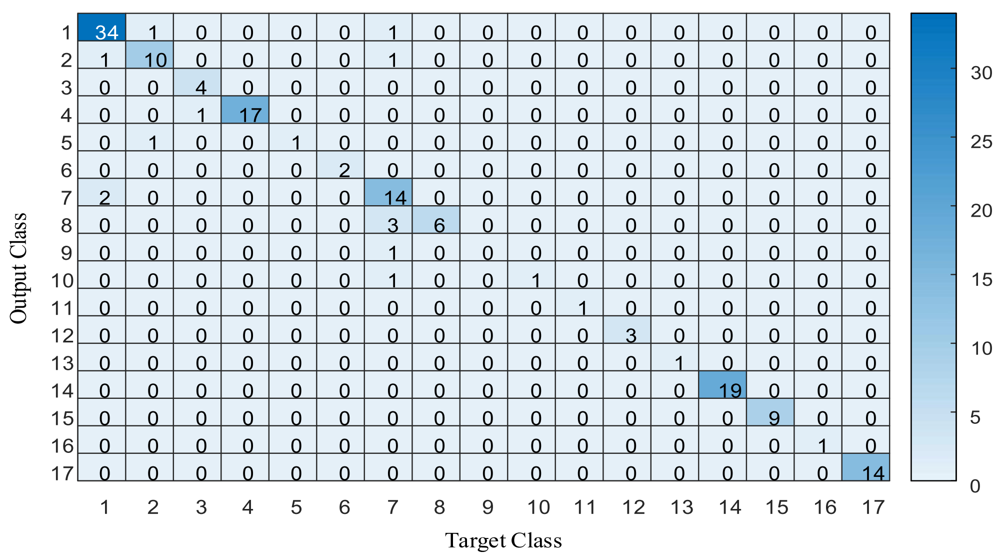

Fig. 6. Confusion matrix of the proposed model for 17-classes using the test data.

signals. In Table 2, the detailed parameter representations of each layer of the proposed deep 16-layer 1D-CNN network are given.

4. Results

For automatic classification of the ECG fragments, the ECG dataset containing 1000 signal fragments (each containing 3600 samples) was used for performance evaluation of the optimized 1D-CNN network. Because of sparse sample numbers in some of the ECG classes in this dataset, two other sub-datasets were created comprising 15 and 13 classes in addition to the original 17-class dataset [45,46]. 70%, 15% and 15% of the data in each sub-datasets were used for training, validation and test phases, respectively, in all experimental studies. Experimental studies were performed on a computer with a 3.40 GHz Intel Xenon E3 1240 v3 machine with 8 GB RAM and Nvidia Quadro K600 GPU unit. The proposed deep network used Keras platform and GPU-based Tensorflow backend.

Table 1 lists the cardiac arrhythmia diagnostic classes in the 1000-ECG signal fragment dataset and the number of ECG signal fragments used by each class in different phases of the experiments. In the 17 -classes dataset comprising 1000 ECG signal fragments, 700 were used in the training stage; 150, validation; and the remaining 150, test phase.

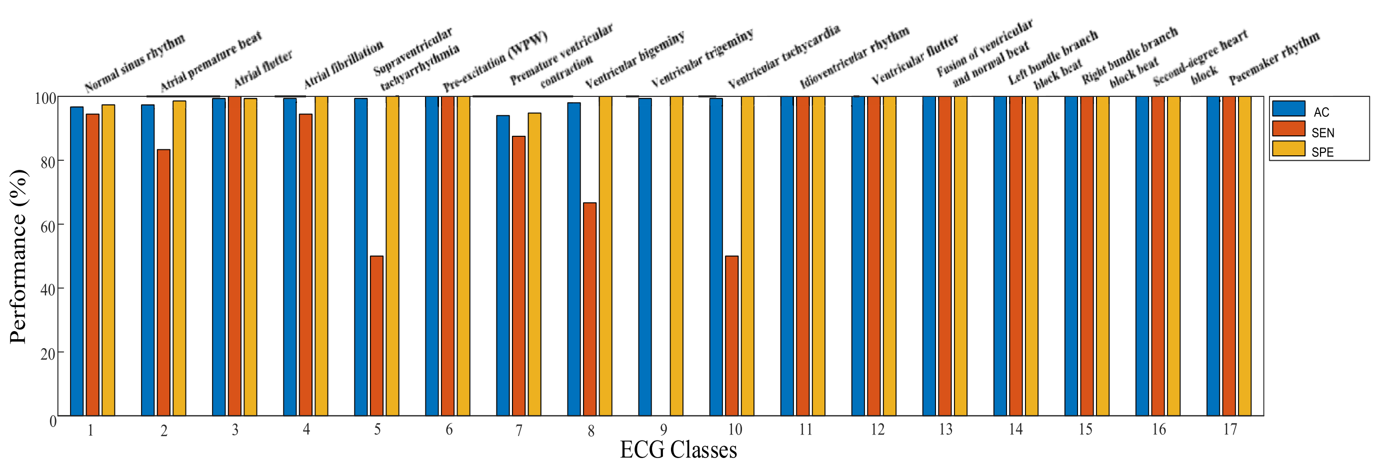

Fig. 7. Graphical representation of the performance parameters for all 17 classes using our proposed method.

The classes "fusion of ventricular and normal beat" and "supraventricular tachyarrhythmia" were removed to create 15-classes sub-dataset comprised of 976 fragments. The 13-classes sub-dataset containing 833 ECG signal fragments was similarly created by removing the four least common classes — "supraventricular tachyarrhythmia", "fusion of ventricular and normal beat", "ventricular tachycardia" and "premature ventricular contraction" classes — from the original 17-classes dataset and this sub-set contains 833 ECG fragments.

The proposed 1D-CNN network was first trained separately using training and validation data for each of the 13, 15 and 17 classes. The validation phase data were used for network parameter tuning. The trained classification network was then applied on data allocated for the testing phase. The data in the testing phase were those that the classifier system had never seen in the educational phase. Fig. 4 shows the training and validation performance graphs of the proposed 16-layer CNN network during 50 epochs for 13-, 15- and 17-classes respectively.

Standard evaluation criteria namely sensitivity (SEN), specificity (SPE), precision, recall, f-score and overall accuracy (AC) were used to assess the performance of the 16-layer 1D-CNN model. Training for all cases attained high accuracy. At the end of 50 epochs for the 13-classes, the training and validation stages attained accuracy rates of 100% and 93.96%, respectively. For the 15-classes, the training and validation accuracy rates were 99.41% and 91.10%, respectively. Finally, 100% training and 86.67% validation accuracy rates were obtained for the 17-classes.

Table 3 details the performance of the 16-layer 1D-CNN classification system on the test data based on the specified evaluation criteria. The SEN of the classifier network for 13-, 15- and 17-classes were 93.52%, 88.57% and 83.91%, respectively. The highest SEN of 93.52% and SPE of 99.61% were obtained for 13-classes. The SPE was more than 99% for all the three cases. Overall accuracies obtained were 95.2%, 92.51% and 91.33% for the 13-, 15- and 17-classes, respectively. Validation and training sets have been randomly selected while adjusting the model's layer and hyper-parameters. Performance measurements are presented for the weights for which the best results are obtained in the study. Based on these results, the proposed 16-layer CNN network provided more than 91% recognition performance for each sub-dataset, including a salutary 91.33% performance for 17-classes. Fig. 5 shows the graphical representation of comparison of performances for different number (13, 15 and 17) of classes used in this study.

Fig. 6 shows the confusion matrix of the proposed model for 17-classes using the test data. The proposed CNN network correctly classified 137 out of 150 fragments belonging to the 17-classes during the testing phase, yielding an overall accuracy of 91.33%. In individual cardiac arrhythmia diagnostic classes 3, 6, 11, 12, 13, 14, 15, 16 and 17, the recognition system provided 100% classification accuracy performance for all.

The lowest recognition performance was observed for the ventricular trigeminy class, which contained only one sample during the testing phase. Since we performed the deep model many times for layer optimization, these results have been presented based on the best weights obtained. The performance values obtained by the proposed CNN network for all the different classes are given in Fig. 7.

5. Discussion

Table 4 summarizes the various published ECG diagnostic algorithms, their respective signal analysis methods and the achieved highest overall accuracies obtained using the same database (MIT-BIH Arrhythmia). The results of our proposed model (in bold) were comparable with best obtained performance, thus confirming the effectiveness of the new 1D-CNN model in classifying the cardiac arrhythmia using long-duration ECG signals.

In the scientific literature, most of the works focuses on recognition of 5 classes. It can be seen from Table 4, that for 17-class recognition, we have obtained the highest accuracy of 91.33% which is comparable

Table 4
Summary of studies performed based on the same database.

Work	Year	Length of signal	No of classes	Feature set	Classifier	Overall AC
de Chazal et al. [79]	2004	198 samples (0.55 s)	5	Morphological, ECG-Intervals	Weighted LD	83%
Park et al. [78]	2008	180 samples (0.50 s)	5	HBF, HOS	Hierarchical SVM	85%
Llamedo and Martinez [28]	2011	120 samples (0.33 s)	5	VCG + SFFS, Wavelet	Weighted LD	93%
Ye, Kumar, and Coimbra [77]	2012	300 samples (0.83 s)	5	Morphological, Wavelet, RR interval, ICA, PCA	SVM	86%
Bazi, Alajlan, AlHichri, and Malek [75]	2013	300 samples (0.83 s)	5	Morphological, Wavelet	SVM, IWKLR, DTSVM	92%
Zhang and Luo [76]	2014	227 samples (0.63 s)	5	ECG-inter. and segments, RR-intervals, wavelet coeff., morph. Features	Combined SVM	87%
Lin and Yang [74]	2014	120 samples (0.33 s)	5	Normalized RR-interval	Weighted LD	93%
Huang et al. [73]	2014	200 samples (0.56 s)	5	RR-intervals, Random projection	Ensemble of SVM	94%
Acharya et al. [1]	2017	360 samples (1 s)	5	Raw data	CNN	94.03%
Yang et al. [83]	2018	300 samples (0.83 s)	5	PCAnet	Linear SVM	97.94%
Oh et al. [72]	2018	Variable Length	5	Raw data	CNN-LSTM	98.10%
Yildirim [62]	2018	360 samples (1 s)	5	Raw data	DBLSTM-WS3	99.39%
Plawiak [46]	2018	3600 samples (10 s)	15	Frequency components of the power spectral density of the ECG [55,59]	Genetic ensemble of SVM classifiers optimized by sets	93.04%
			17			91.40%
Plawiak [45]	2018	3600 samples (10 s)	13	Frequency components of the power spectral density of the ECG [55,59]	Evolutionary-Neural System (based on SVM)	94.60%
			15			91.28%
			17			90.20%
Proposed method		**3600 samples (10 s)**	**13**	**Rescaling raw data**	**1D-CNN**	**95.20%**
			15			**92.51%**
			17			**91.33%**

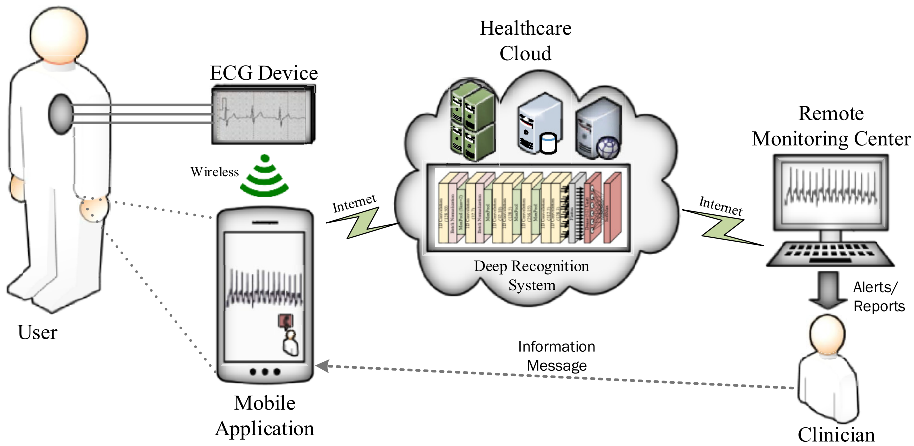

Fig. 8. An illustration of using of the proposed long-duration ECG recognition system in a clinical scenario.

(91.40%) to a more complex ensemble of classifiers [46]. Our results were better than the previous work by Plawiak [45] for 17, 15 and 13-classes also. The time required for the classification of a single 10-s ECG signal fragment using 1D-CNN was 0.015 s. This short computation time is very promising for potential application of the proposed solution in tele-medicine and mobile devices or cloud computing for real-time continuous ECG signal analysis.

The proposed method (1D-CNN) is less complex, simpler to use and more optimized (end-to-end structure in which classification and feature extraction and selection stages were combined) compared to the methods described in Refs. [45,46]. Additionally, the proposed method achieved better overall accuracy than the evolutionary-neural system [45] and a comparable overall accuracy with complex ensemble of classifiers [46].

Our proposed model can be employed in the clinical scenario as shown in Fig. 8. The patient ECG can be acquired and sent through the mobile phone to the cloud where our developed model is trained and kept. The results of the diagnosis can be validated by the clinicians in the hospital immediately by reading the ECG beats. The hospital will send a message to the patient to see the clinician if they find any abnormal ECG beats. Hence, the patient is always closely monitored.

This new methodology has the following advantages:

(i) the number of classifications (analysis) was reduced; and the need to detect and segment QRS complexes, obviated. As a result, computational complexity was reduced, which potentially facilitate the application of the proposed solution for real-time signal processing on mobile devices and cloud computing (see Fig. 8).
(ii) the analysis of longer-duration ECG signal fragments may yield more accurate classification for some diseases that are more likely to have time-varying ECG signal changes, e.g. pre-excitation syndromes, atrio-ventricular conduction blocks [45].

The main disadvantages of this study are:

(i) small number of ECG signal fragments (1000 from 45 patients) are analyzed.
(ii) no possibility of classifying fragments of ECG signal containing more than one class.

6. Conclusion

The goal of the study was to design a deep learning 1D-CNN that is able to classify cardiac arrhythmia (17 diagnostic classes encompassing “normal sinus rhythm”, “pacemaker rhythm” and 15 other rhythm disorders) effectively from analysis of long-duration (10-s) ECG signal fragments.

The proposed method is: (i) efficient; (ii) fast (real-time classification); (iii) universal; (iv) simple to use; and (v) highly accurate.

1D-CNN model achieved an overall classification accuracy of 91.33% for 17 cardiac arrhythmia (classes), with classification time of 0.015 s for analysis of each 10-s ECG sample. Compared to published research, our results are one of the best to date and our solution can be feasibly implemented in mobile devices and cloud computing. The high accuracy rate is achieved in spite of using large number diagnostic classes (up to 17 classes of cardiac disorders) with less number of data in a few classes.

Our novel 1D-CNN model exhibits high performance for classification of multiple cardiac arrhythmia disorders, and yet is simple to use due to its lower computational complexity. The potential to use our solution in tele-medicine, especially in mobile devices and cloud computing for monitoring of ECG signals from a single lead, underscores the strength of this research.

The promising results will motivate continued exploration. The future works will include (i) increasing the performance of classification of heart disorders by designing and modifying methods based on deep learning, ensemble learning and evolutionary computation; (ii) testing the efficiency of developed 1D-CNN using other physiological signals, (iii) classifying fragments of the ECG signal that containing more than one class, and (iv) testing the performance of the developed model with more number of fragments of ECG signal.

Conflicts of interest

There is no conflict of interest in this work.

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