

See discussions, stats, and author profiles for this publication at: <https://www.researchgate.net/publication/327602644>

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

Article in *Computers in Biology and Medicine* · September 2018

DOI: 10.1016/j.combiomed.2018.09.009

CITATIONS

83

READS

3,731

4 authors, including:



**Paweł Pławiak**

Cracow University of Technology

37 PUBLICATIONS 454 CITATIONS

[SEE PROFILE](#)



**Ru San Tan**

National Heart Centre Singapore

323 PUBLICATIONS 5,378 CITATIONS

[SEE PROFILE](#)



**U Rajendra Acharya**

Ngee Ann, Singapore University of Social Science, Singapore; University of Malaya...

642 PUBLICATIONS 20,649 CITATIONS

[SEE PROFILE](#)

Some of the authors of this publication are also working on these related projects:



Efficient Detection of Congestive Heart Failure [View project](#)



FFRb: Validation of a Predictive Model of Coronary Fractional Flow Reserve in Patients With Intermediate Coronary Stenosis [View project](#)

# **ARRHYTHMIA DETECTION USING DEEP CONVOLUTIONAL NEURAL NETWORK WITH LONG DURATION ECG SIGNALS**

Özal Yıldırım<sup>a\*</sup>, Paweł Pławiak<sup>b</sup>, Ru-San Tan<sup>c,d</sup>, U Rajendra Acharya<sup>e,f,g</sup>

<sup>a</sup> Department of Computer Engineering, Munzur University, Tunceli, Turkey

<sup>b</sup> Institute of Telecomputing, Faculty of Physics, Mathematics and Computer Science  
Cracow University of Technology, Krakow, Poland

<sup>c</sup> Department of Cardiology, National Heart Centre Singapore, Singapore

<sup>d</sup> Duke-NUS Medical School, Singapore

<sup>e</sup> Department of Electronics and Computer Engineering, Ngee Ann Polytechnic, Singapore

<sup>f</sup> Department of Biomedical Engineering, School of Science and Technology, Singapore School of  
Social Sciences, Singapore

<sup>g</sup> School of Medicine, Faculty of Health and Medical Sciences, Taylor's University, 47500 Subang  
Jaya, Malaysia.

\* Corresponding author. Tel.: +90-428 -2131794; fax: +90-428-2131861.

*E-mail address:* [oyildirim@munzur.edu.tr](mailto:oyildirim@munzur.edu.tr), [yildirimoza@hotmail.com](mailto:yildirimoza@hotmail.com)

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

Özal Yıldırım<sup>a,\*</sup>, Paweł Pławiak<sup>b</sup>, Ru-San Tan<sup>c,d</sup>, U Rajendra Acharya<sup>e,f,g</sup>

<sup>a</sup> Department of Computer Engineering, Munzur University, Tunceli, Turkey

<sup>b</sup> Institute of Telecomputing, Faculty of Physics, Mathematics and Computer Science Cracow University of Technology, Krakow, Poland

<sup>c</sup> Department of Cardiology, National Heart Centre Singapore, Singapore

<sup>d</sup> Duke-NUS Medical School, Singapore

<sup>e</sup> Department of Electronics and Computer Engineering, Ngee Ann Polytechnic, Singapore

<sup>f</sup> Department of Biomedical Engineering, School of Science and Technology, Singapore School of Social Sciences, Singapore

<sup>g</sup> School of Medicine, Faculty of Health and Medical Sciences, Taylor's University, 47500 Subang Jaya, Malaysia.

Email Address: [oyildirim@munzur.edu.tr](mailto:oyildirim@munzur.edu.tr), [yildirimoza@hotmail.com](mailto:yildirimoza@hotmail.com)

## 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 the 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 is 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). 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 sec. 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.

*Keywords:* cardiac arrhythmias, ECG classification, deep learning, convolutional neural networks.

## 1. Introduction

Electrocardiography (ECG) is the most basic and accessible method of diagnosing cardiac arrhythmia (or heart rhythm disorders), as it is 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], [67], [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 [67], [68], [66], [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.

Deep learning [10], [16], [7], [8], [54], [26], [4] 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) [62, 72, 47, 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 to ECG: (i) classification or detection of ECG beat [32], [33], [63], [56], [5]; (ii) deep learning [3], [23], [48]; (iii) principal component analysis [34], [35], [32], [22], [21], [58], [12], [49]; (iv) higher order statistics [36], [37], [38]; (v) feature selection/dimensionality reduction [39], [64], [24], [28], [31], [11], [65], [61]; (vi) noise [44], [27], [50]; (vii) discrete wavelet transform [25], [60], [41], [12], [19], [57], [32], [9]; (viii) independent component analysis [53], [12], [32]; and (ix) ensemble learning [46], [52], [18], [20], [40].

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 [30], [29], [6], 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 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).

In [45] single machine learning methods and in [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

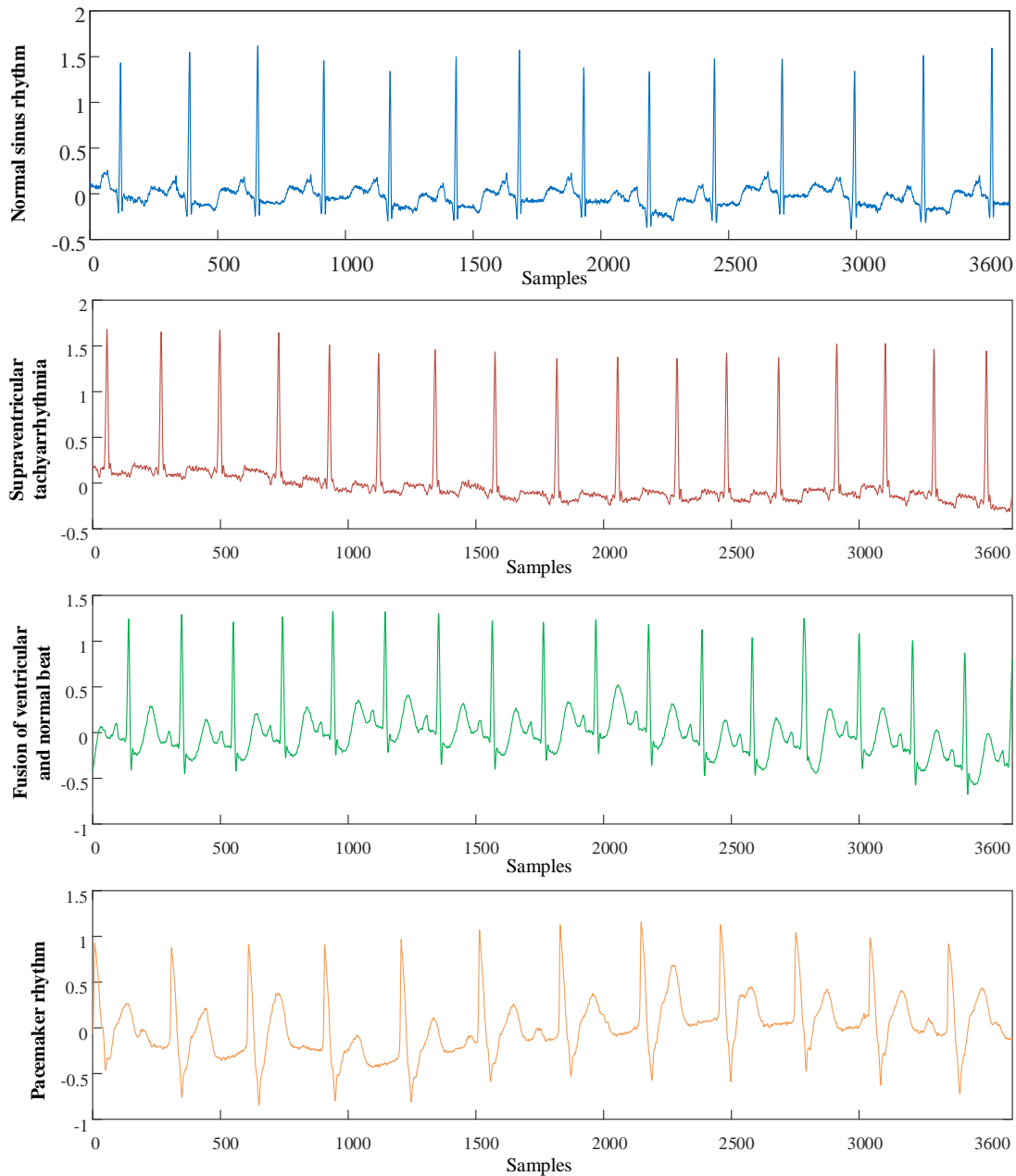
From the MIT-BIH Arrhythmia database [42], hosted at PhysioNet (<http://www.physionet.org>) [14], ECG signals were acquired. The research ECG dataset comprised 3600 10-s non-overlapping samples extracted from 1000 randomly-selected ECG signal fragments that had been recorded at sampling frequency of 360 Hz and gain of 200  $\mu$ V / 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.** 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
	<b>Total</b>	1000	583	125	125	680	149	147	700	150	150

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

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 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.



**Figure 1.** Typical signal samples of different classes.



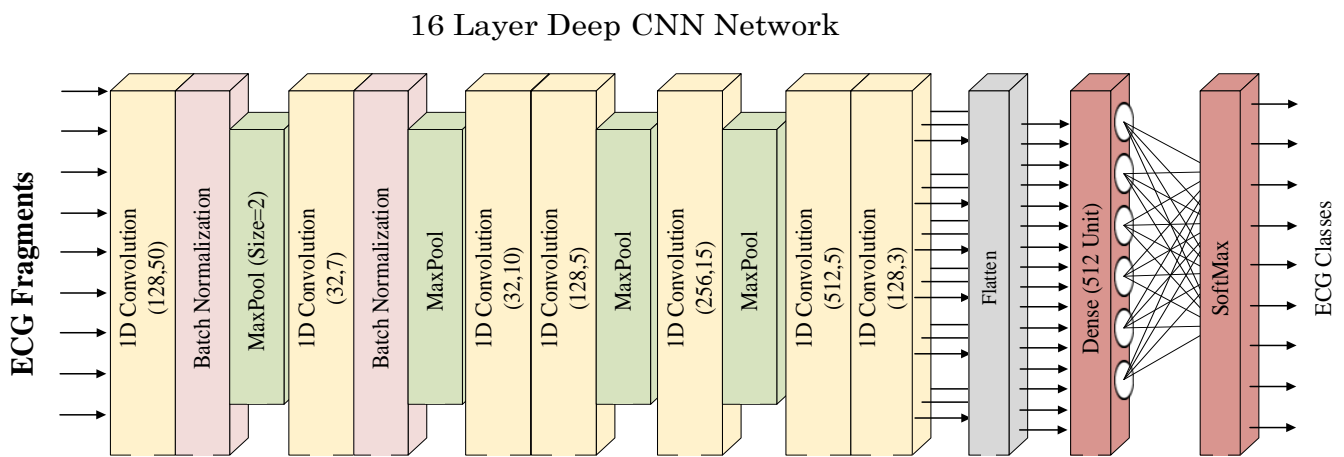
### 3.3 Methods

#### 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

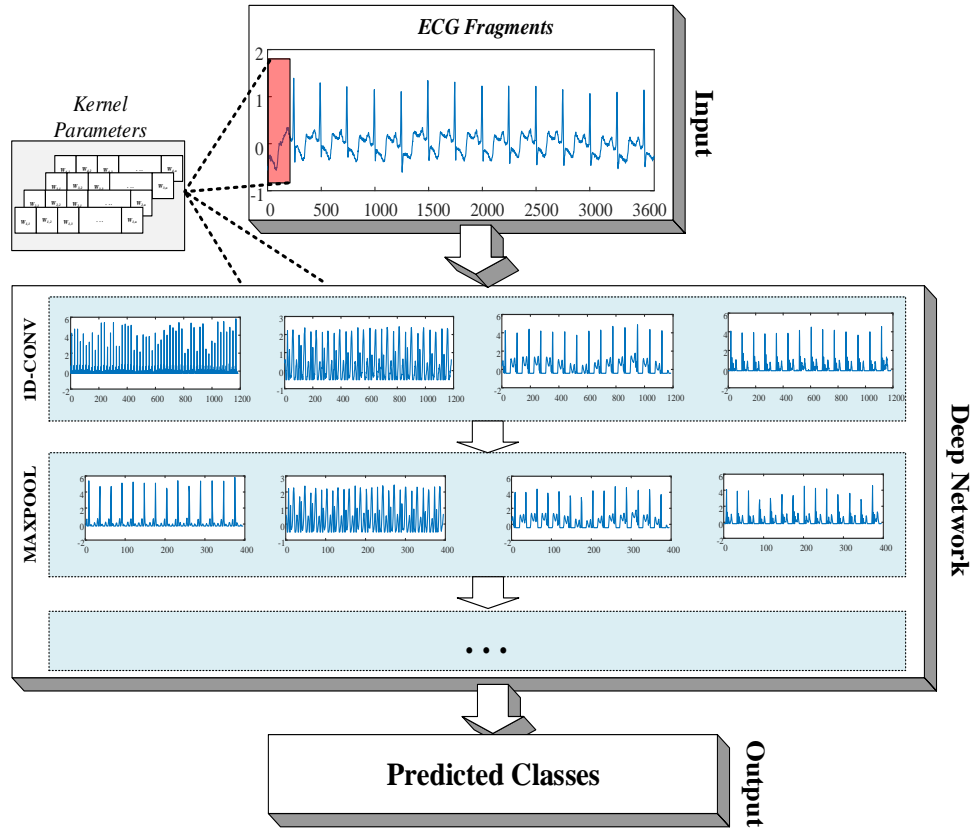
A 16-layer deep convolutional network was designed for the classification of ECG signals according to cardiac arrhythmia. This deep network model provides automatic classification of input fragments through an end-to-end structure without the need for any hand-crafted feature extraction or selection 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.



**Figure 2.** Block diagram of the proposed 16 layer CNN model.

In the first layer of the model, 1D convolution is performed with 128 weight 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.



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

In the fourth layer, the convolution process is repeated on the input feature maps with  $32 \times 7$ -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 developed 16-layer model, yielded the highest classification results for long duration ECG signals. In Table 2, the detailed parameter representations of each layer of the proposed deep 16-layer 1D-CNN network are given.

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

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

#### 4. Results

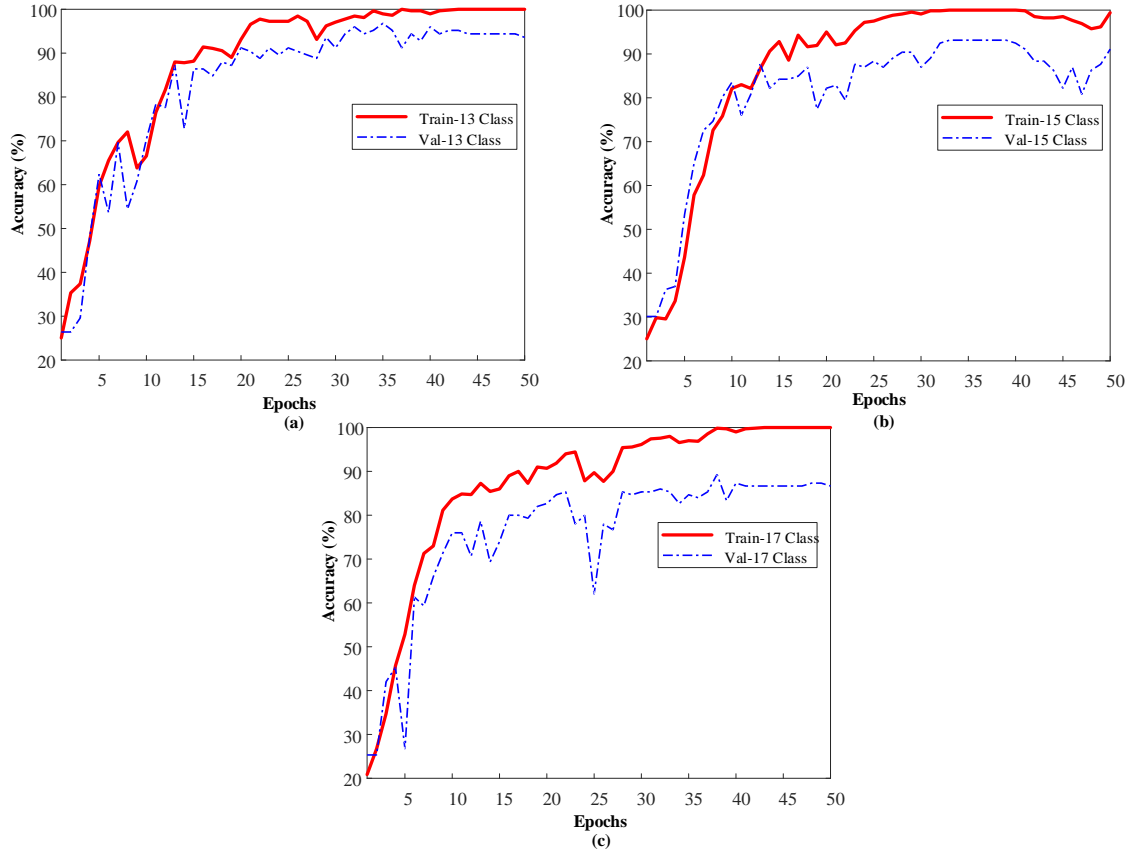
For automatic classification of the ECG fragments, the ECG dataset containing 1000 signal fragments (each containing 3600 samples) was used for performance evaluation of the optimized 1D-CNN network. Because of sparse sample numbers in some of the ECG classes in this dataset, two other sub-datasets were 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. 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 is 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.



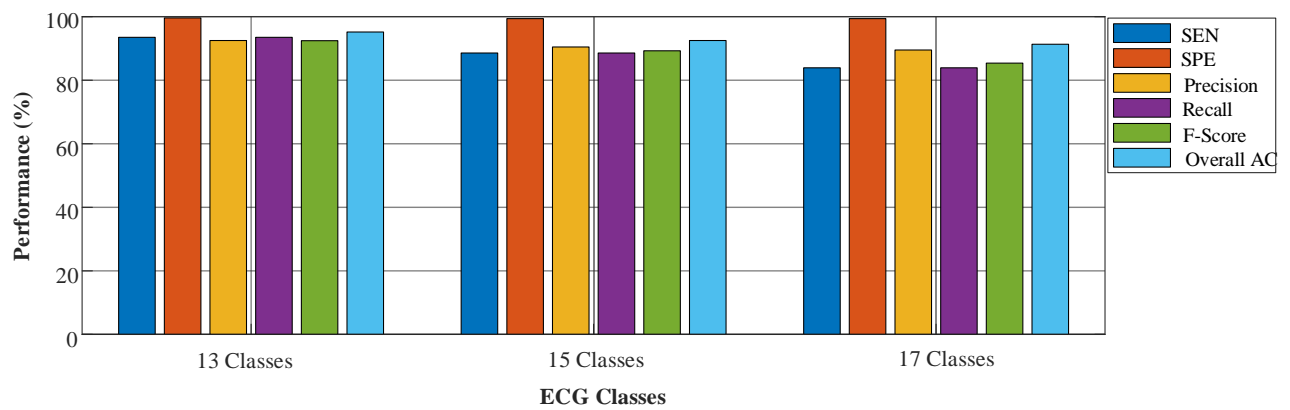
**Figure 4.** Training and validation performances using our proposed model with ECG datasets: (a) 13-classes, (b) 15-classes, c) 17-classes.

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

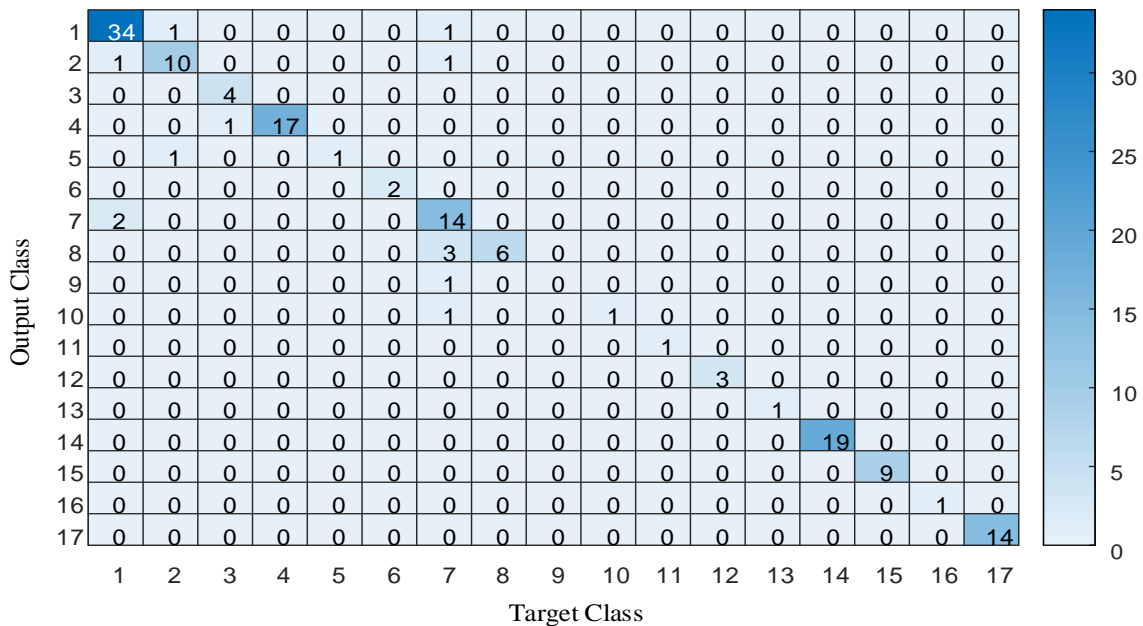
Classes	SEN(%)	SPE (%)	Precision(%)	Recall (%)	F-Score (%)	Overall AC(%)
<b>13-Classes</b>	93.52	99.61	92.52	93.52	92.45	95.2
<b>15-Classes</b>	88.57	99.39	90.48	88.57	89.28	92.51
<b>17-Classes</b>	83.91	99.41	89.52	83.91	85.38	91.33

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.



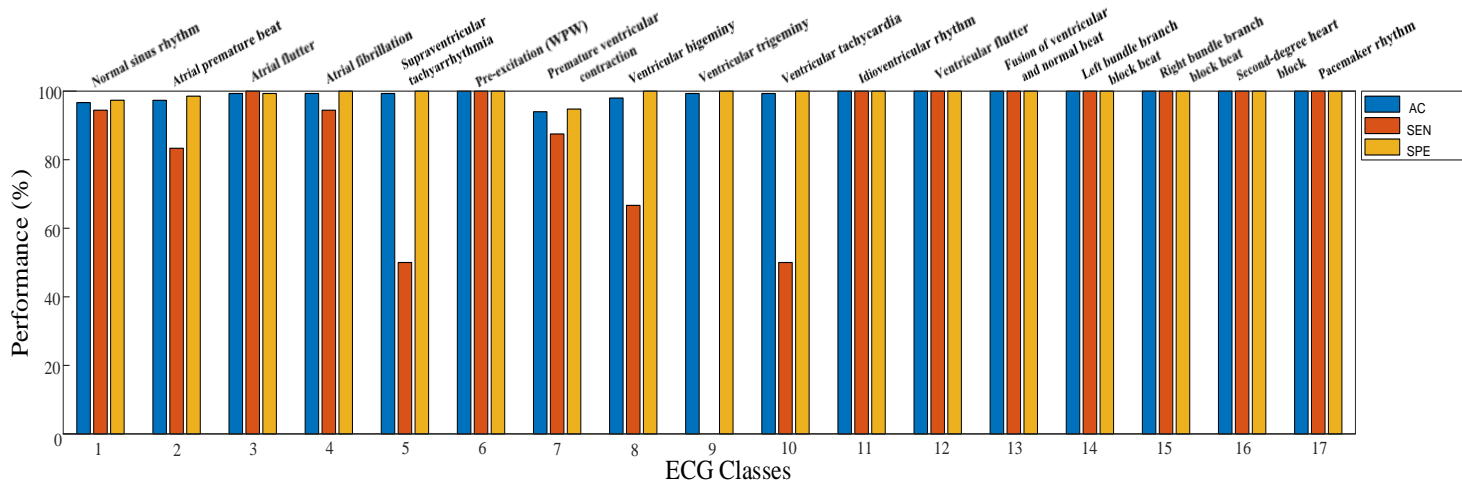
**Figure 5.** Graphical representation of classification performances for different number (13,15 and 17) of classes using the proposed model.



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

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.



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

## 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 new 1D-CNN model in classifying the cardiac arrhythmia using long-duration ECG signals.

**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 17	Frequency components of the power spectral density of the ECG	Genetic ensemble of SVM classifiers optimized by sets	93.04% 91.40%
Plawiak [45]	2018	3600 samples (10 s)	13 15 17	Frequency components of the power spectral density of the ECG	Evolutionary-Neural System (based on SVM)	94.60% 91.28% 90.20%
Proposed method		3600 samples (10 s)	13 15 17	Rescaling raw data	1D-CNN	95.20% 92.51% 91.33%



In the scientific literature, most of the works focuses on recognition of 5 classes. It can be seen from the table 4, that for 17-class recognition, we have obtained the highest accuracy of 91.33% which is comparable (91.40%) to a more complex ensemble of classifiers [46]. Even our result has better than 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, and simpler to use and optimize (end-to-end structure in which classification and feature extraction and selection stages were combined), compared to the methods described in [45-46]. Additionally, proposed method achieved better overall accuracy than the evolutionary-neural system [45] and a comparable overall accuracy with complex ensemble of classifiers [46].

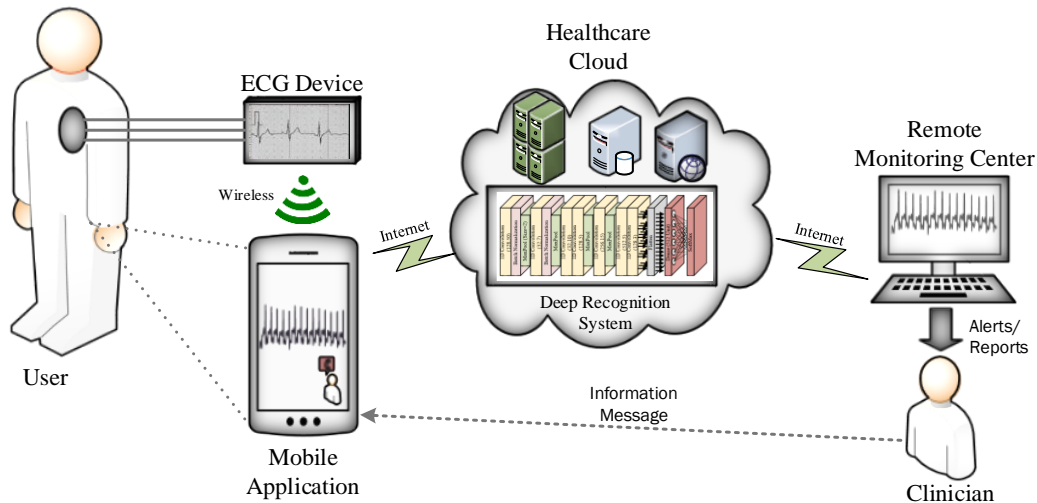
Our proposed model can be employed in the clinical scenario as shown in Fig. 8. The patient ECG can be acquired and sent through the mobile phone to the cloud where our developed model is trained and kept. The results of the diagnosis can be validated by the clinicians in the hospital immediately by 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.



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

## 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) high accuracy.

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 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.

## References

1. Acharya, U. R., Oh, S. L., Hagiwara, Y., Tan, J. H., Adam, M., Gertych, A., & San Tan, R. (2017). A deep convolutional neural network model to classify heartbeats. *Computers in biology and medicine*, 89, 389-396.
2. Acharya, U. R., Fujita, H., Oh, S. L., Hagiwara, Y., Tan, J. H., & Adam, M. (2017). Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals. *Information Sciences*, 415, 190-198.
3. Acharya, U. R., Fujita, H., Lih, O. S., Hagiwara, Y., Tan, J. H., & Adam, M. (2017). Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network. *Information sciences*, 405, 81-90.
4. Arel, I., Rose, D. C., & Karnowski, T. P. (2010). Deep machine learning-a new frontier in artificial intelligence research. *IEEE computational intelligence magazine*, 5(4), 13-18.
5. Augustyniak, P. (2015). A robust heartbeat detector not depending on ECG sampling rate. In *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE* (pp. 7861-7864).
6. Augustyniak, P., & Tadeusiewicz, R. (2009). Background 1: ECG Interpretation. In *Ubiquitous Cardiology: Emerging Wireless Telemedical Applications* (pp. 11-71). IGI Global.
7. Bengio, Y. (2009). Learning deep architectures for AI. *Foundations and trends in Machine Learning*, 2(1), 1-127.
8. Bengio, Y., Courville, A., & Vincent, P. (2013). Representation learning: A review and new perspectives. *IEEE transactions on pattern analysis and machine intelligence*, 35(8), 1798-1828.
9. Daamouche, A., Hamami, L., Alajlan, N., & Melgani, F. (2012). A wavelet optimization approach for ECG signal classification. *Biomedical Signal Processing and Control*, 7(4), 342-349.
10. Hinton, Geoffrey E. and Osindero, Simon and Teh, Yee-Whye; A Fast Learning Algorithm for Deep Belief Nets; *Neural Comput.*; 2006; 18; 1527-1554
11. G. Doquire and G. de Lannoy and D. Francois and M. Verleysen; Feature Selection for Interpatient Supervised Heart Beat Classification; *Computational Intelligence and Neuroscience*; 2011; 2011; 1-9
12. Fatin A. Elhaj and Naomie Salim and Arief R. Harris and Tan Tian Swee and Taqwa Ahmed; Arrhythmia recognition and classification using combined linear and nonlinear features of ECG signals; *Computer Methods and Programs in Biomedicine*; 2016; 127; 52-63
13. Uçar, A., Demir, Y., & Güzeliş, C. (2017). Object recognition and detection with deep learning for autonomous driving applications. *Simulation*, 93(9), 759-769.

14. Goldberger, A. L. and Amaral, L. A. N. and Glass, L. and Hausdorff, J. M. and Ivanov, P. Ch. and Mark, R. G. and Mietus, J. E. and Moody, G. B. and Peng, C.-K. and Stanley, H. E.; PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals; *Circulation*; 2000; 101; e215—e220
15. C. Goller and A. Kuchler; Learning task-dependent distributed representations by backpropagation through structure; *Neural Networks*, 1996., IEEE International Conference on; 1996; 1; 347-352
16. Ian Goodfellow and Yoshua Bengio and Aaron Courville; *Deep Learning*; Book in preparation for MIT Press; 2016
17. Hinton, Geoffrey E.; A Practical Guide to Training Restricted Boltzmann Machines; Montavon, Gregoire and Orr, Genevieve B. and Muller, Klaus-Robert; *Neural Networks: Tricks of the Trade: Second Edition*; Springer Berlin Heidelberg; 2012; 599-619
18. H. Huang and J. Liu and Q. Zhu and R. Wang and G. Hu; A new hierarchical method for inter-patient heartbeat classification using random projections and RR intervals; *Biomed. Eng. Online*; 2014; 13; 1-26
19. M. K. Islam and A. N. M. M. Haque and G. Tangim and T. Ahammad and M. R. H. Khondokar; Study and Analysis of ECG Signal Using MATLAB & LABVIEW as Effective Tools; *International Journal of Computer and Electrical Engineering (IJCEE)*; 2012; 4; 404-408
20. Mehrdad Javadi and Seyed Ali Asghar Abbaszadeh Arani and Atena Sajedin and Reza Ebrahimpour; Classification of ECG arrhythmia by a modular neural network based on Mixture of Experts and Negatively Correlated Learning; *Biomedical Signal Processing and Control*; 2013; 8; 289 – 296
21. M. Kallas and C. Francis and P. Honeine and H. Amoud and C. Richard; Modeling electrocardiogram using Yule-Walker equations and kernel machines; *Telecommunications (ICT)*, 2012 19th International Conference on; 2015; 1-5
22. L. Kanaan and D. Merheb and M. Kallas and C. Francis and H. Amoud and P. Honeine; PCA and KPCA of ECG signals with binary SVM classification; *Signal Processing Systems (SiPS)*, 2011 IEEE Workshop on; 2011; 344-348
23. Yildirim, O., San Tan, R., & Acharya, U. R. (2018). An efficient compression of ECG signals using deep convolutional autoencoders. *Cognitive Systems Research*, 52, 198-211.
24. Naval Kishore and Sukhmanpreet Singh; Cardiac Analysis and Classification of ECG Signal using GA and NN; *International Journal of Computer Applications*; 2015; 127; 23-27
25. Y. Kutlu and D. Kuntalp; Feature extraction for ECG heartbeats using higher order statistics of WPD coefficients; *Computer Methods and Programs in Biomedicine*; 2012; 105; 257 – 267
26. Yann LeCun and Yoshua Bengio and Geoffrey Hinton; Deep learning; *Nature*; 2015; 521; 436-444
27. Qiao Li and Cadathur Rajagopalan and Gari D. Clifford; A machine learning approach to multi-level ECG signal quality classification; *Computer Methods and Programs in Biomedicine*; 2014; 117; 435 – 447
28. M. Llamedo and J. P. Martinez; Heartbeat Classification Using Feature Selection Driven by Database Generalization Criteria; *IEEE Transactions on Biomedical Engineering*; 2011; 58; 616-625
29. Eduardo Jose da S. Luz and William Robson Schwartz and Guillermo Camara-Chavez and David Menotti; ECG-based heartbeat classification for arrhythmia detection: A survey; *Computer Methods and Programs in Biomedicine*; 2016; 127; 144 – 164

30. Eduardo Jose da S. Luz and Thiago M. Nunes and Victor Hugo C. de Albuquerque and Joao P. Papa and David Menotti; ECG arrhythmia classification based on optimum-path forest; *Expert Systems with Applications*; 2013; 40; 3561 – 3573
31. Yildirim, Ö, and Baloglu, U. B., “Heartbeat type classification with optimized feature vectors”, *An International Journal of Optimization and Control: Theories & Applications (IJOCTA)*, vol. 8(2), 170-175, 2018.
32. Roshan Joy Martis and U. Rajendra Acharya and Lim Choo Min; ECG beat classification using PCA, LDA, ICA and Discrete Wavelet Transform; *Biomedical Signal Processing and Control*; 2013; 8; 437 – 448
33. Roshan Joy Martis and U. Rajendra Acharya and Hojjat Adeli; Current methods in electrocardiogram characterization; *Computers in Biology and Medicine*; 2014; 48; 133 – 149
34. Roshan Joy Martis and U. Rajendra Acharya and K.M. Mandana and A.K. Ray and Chandan Chakraborty; Application of principal component analysis to ECG signals for automated diagnosis of cardiac health; *Expert Systems with Applications*; 2012; 39; 11792 – 11800
35. Roshan Joy Martis and U. Rajendra Acharya and Choo Min Lim and Jasjit S. Suri; Characterization of ECG beats from cardiac arrhythmia using discrete cosine transform in PCA framework; *Knowledge-Based Systems*; 2013; 45; 76 – 82
36. Roshan Joy Martis and U. Rajendra Acharya and K.M. Mandana and A.K. Ray and Chandan Chakraborty; Cardiac decision making using higher order spectra; *Biomedical Signal Processing and Control*; 2013; 8; 193 – 203
37. R. J. Martis and U. R. Acharya and A. K. Ray and C. Chakraborty; Application of higher order cumulants to ECG signals for the cardiac health diagnosis; 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society; 2011; 1697-1700
38. Roshan Joy Martis and U. Rajendra Acharya and Hari Prasad and Chua Kuang Chua and Choo Min Lim and Jasjit S. Suri; Application of higher order statistics for atrial arrhythmia classification; *Biomedical Signal Processing and Control*; 2013; 8; 888 – 900
39. Roshan Joy Martis and U. Rajendra Acharya and Hojjat Adeli and Hari Prasad and Jen Hong Tan and Kuang Chua Chua and Chea Loon Too and Sharon Wan Jie Yeo and Louis Tong; Computer aided diagnosis of atrial arrhythmia using dimensionality reduction methods on transform domain representation; *Biomedical Signal Processing and Control*; 2014; 13; 295 – 305
40. Mert, Ahmet and Klc, Niyazi and Akan, Aydn; Evaluation of bagging ensemble method with time-domain feature extraction for diagnosing of arrhythmia beats; *Neural Computing and Applications*; 2012; 24; 317-326
41. Akanksha Mishra and Falgun Thakkar and Chintan Modi and Rahul Kher; Comparative Analysis of Wavelet Basis Functions for ECG Signal Compression through Compressive Sensing; *International Journal of Computer Science and Telecommunications*; 2012; 3; 23-31
42. G. B. Moody and R. G. Mark; The impact of the MIT-BIH Arrhythmia Database; *IEEE Engineering in Medicine and Biology Magazine*; 2001; 20; 45-50
43. K. Padmavathi and K. Sri Ramakrishna; Classification of ECG Signal during Atrial Fibrillation Using Autoregressive Modeling; *Procedia Computer Science*; 2015; 46; 53 – 59
44. Edoardo Pasolli and Farid Melgani; Genetic algorithm-based method for mitigating label noise issue in ECG signal classification; *Biomedical Signal Processing and Control*; 2015; 19; 130-136

45. Paweł Pławiak; Novel methodology of cardiac health recognition based on ECG signals and evolutionary-neural system; *Expert Systems with Applications*; 2018; 92; 334 – 349
46. Paweł Pławiak; Novel genetic ensembles of classifiers applied to myocardium dysfunction recognition based on ECG signals; *Swarm and Evolutionary Computation*; 2018; 39; 192 – 208
47. Faust, O., Shenfield, A., Kareem, M., San, T. R., Fujita, H., & Acharya, U. R. (2018). Automated detection of atrial fibrillation using long short-term memory network with RR interval signals. *Computers in biology and medicine*.
48. M.M. Al Rahhal and Yakoub Bazi and Haikel AlHichri and Naif Alajlan and Farid Melgani and R.R. Yager; Deep learning approach for active classification of electrocardiogram signals; *Information Sciences*; 2016; 345; 340 – 354
49. R. Rodriguez and A. Mexicano and J. Bila and S. Cervantes and R. Ponce; Feature Extraction of Electrocardiogram Signals by Applying Adaptive Threshold and Principal Component Analysis; *Journal of Applied Research and Technology*; 2015; 13; 261 – 269
50. E. Kheirati Roonizi and R. Sassi; A Signal Decomposition Model-Based Bayesian Framework for ECG Components Separation; *IEEE Transactions on Signal Processing*; 2016; 64; 665-674
51. Ruslan Salakhutdinov and Geoffrey Hinton; Deep Boltzmann Machines; David van Dyk and Max Welling; *Proceedings of Machine Learning Research*; PMLR; 2009; 5; 448–455
52. D. Sambhu and A. C. Umesh; Automatic Classification of ECG Signals with Features Extracted Using Wavelet Transform and Support Vector Machines; *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*; 2013; 2; 235-241
53. M. Sarfraz and A. A. Khan and F. F. Li; Using independent component analysis to obtain feature space for reliable ECG Arrhythmia classification; *Bioinformatics and Biomedicine (BIBM)*, 2014 IEEE International Conference on; 2014; 62-67
54. Jurgen Schmidhuber; Deep learning in neural networks: An overview; *Neural Networks*; 2015; 61; 85 – 117
55. Steven Smith; *Digital Signal Processing: A Practical Guide for Engineers and Scientists*; 2002
56. Mi-Hye Song and Sung-Pil Cho and Wonky Kim and Kyoung-Joung Lee; New real-time heartbeat detection method using the angle of a single-lead electrocardiogram; *Computers in Biology and Medicine*; 2015; 59; 73 – 79
57. Manu Thomas and Manab Kr Das and Samit Ari; Automatic ECG arrhythmia classification using dual tree complex wavelet based features; *AEU - International Journal of Electronics and Communications*; 2015; 69; 715 – 721
58. Jeen-Shing Wang and Wei-Chun Chiang and Yu-Liang Hsu and Ya-Ting C. Yang; ECG arrhythmia classification using a probabilistic neural network with a feature reduction method; *Neurocomputing*; 2013; 116; 38-45
59. P. Welch; The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms; *IEEE Transactions on Audio and Electroacoustics*; 1967
60. Jihong Yan and Lei Lu; Improved Hilbert-Huang transform based weak signal detection methodology and its application on incipient fault diagnosis and ECG signal analysis; *Signal Processing*; 2014; 98; 74 – 87
61. Yun-Chi Yeh and Wen-June Wang and Che Wun Chiou; Feature selection algorithm for ECG signals using Range-Overlaps; *Expert Systems with Applications Method*; 2010; 37; 3499 – 3512

62. Ozal Yildirim; A novel wavelet sequences based on deep bidirectional LSTM network model for ECG signal classification; Computers in Biology and Medicine; 2018; 96; 189 – 202
63. Maxime Yochum and Charlotte Renaud and Sabir Jacquir; Automatic detection of P, QRS and T patterns in 12 leads ECG signal based on CWT; Biomedical Signal Processing and Control; 2016; 25; 46-52
64. Sung-Nien Yu and Ming-Yuan Lee; Bispectral analysis and genetic algorithm for congestive heart failure recognition based on heart rate variability; Computers in Biology and Medicine; 2012; 42; 816 – 825
65. Zhancheng Zhang and Jun Dong and Xiaoqing Luo and Kup-Sze Choi and Xiaojun Wu; Heartbeat classification using disease-specific feature selection; Computers in Biology and Medicine; 2014; 46; 79 – 89
66. Heart Disease, Stroke and Research Statistics At-a-Glance; AHA; 2016
67. International Cardiovascular Disease Statistics; AHA; 2003
68. WHO GLOBAL STATUS REPORT on noncommunicable diseases; WHO; 2014
69. Deaths: Leading causes for 2003; Hyattsville, MD: National Center for Health Statistics; 2003; Heron, M. P. and Smith, B. L.
70. Health, United States, 2005 with chartbook on the health of Americans; Hyattsville, MD; 2005; National Center for Health Statistics
71. Healthsquare; Heart disease; Conference on Computational Intelligence for Modelling Control and Automation; 2007; 179-182
72. S. L. Oh, E. Y. Ng, R. S. Tan, & U. R. Acharya, “Automated diagnosis of arrhythmia using combination of CNN and LSTM techniques with variable length heart beats”, Computers in Biology and Medicine, 2018.
73. H. Huang and J. Liu and Q. Zhu and R. Wang and G. Hu; A new hierarchical method for inter-patient heartbeat classification using random projections and RR intervals; Biomed. Eng. Online; 2014; 13; 1-26
74. C. C. Lin and C. M. Yang; Heartbeat Classification Using Normalized RR Intervals and Wavelet Features; Computer, Consumer and Control (IS3C), 2014 International Symposium on; 2014; 650-653
75. Y. Bazi and N. Alajlan and H. AlHichri and S. Malek; Domain adaptation methods for ECG classification; Computer Medical Applications (ICMA), 2013 International Conference on; 2013; 1-4
76. Zhang, Zhancheng and Luo, Xiaoqing; Heartbeat classification using decision level fusion; Biomedical Engineering Letters; 2014; 4; 388-395
77. C. Ye and B. V. K. V. Kumar and M. T. Coimbra; Combining general multi-class and specific two-class classifiers for improved customized ECG heartbeat classification; Pattern Recognition (ICPR), 2012 21st International Conference on; 2012; 2428-2431
78. K. S. Park and B. H. Cho and D. H. Lee and S. H. Song and J. S. Lee and Y. J. Chee and I. Y. Kim and S. I. Kim; Hierarchical support vector machine based heartbeat classification using higher order statistics and hermite basis function; Computers in Cardiology, 2008; 2008; 229-232
79. Philip de Chazal and M. O'Dwyer and R. B. Reilly; Automatic classification of heartbeats using ECG morphology and heartbeat interval features; IEEE Transactions on Biomedical Engineering; 2004; 51; 1196-1206

80. Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, Gradient-based learning applied to document recognition, *Proceedings of the IEEE*, 86(1998), 2278-2324.
81. Y. Bengio, Learning deep architectures for AI, *Foundations and Trends in Machine Learning*, 2(2009) 1-127.
82. M. Coşkun, A. Uçar, Ö. Yıldırım, & Y. Demir, Face Recognition Based on Convolutional Neural Network, *International Conference on Modern Electrical and Energy Systems*, 2017.
83. Yang, W., Si, Y., Wang, D., & Guo, B. (2018). Automatic recognition of arrhythmia based on principal component analysis network and linear support vector machine. *Computers in Biology and Medicine*
84. Faust, O., Hagiwara, Y., Hong, T. J., Lih, O. S., & Acharya, U. R. (2018). Deep learning for healthcare applications based on physiological signals: a review. *Computer methods and programs in biomedicine*.
85. Abdel-Hamid, O., Mohamed, A. R., Jiang, H., Deng, L., Penn, G., & Yu, D. (2014). Convolutional neural networks for speech recognition. *IEEE/ACM Transactions on audio, speech, and language processing*, 22(10), 1533-1545.
86. Coşkun, M., Yıldırım, Ö., Uçar, A., & Demir, Y. (2017). An Overview of Popular Deep Learning Methods. *European Journal of Technique*, 7(2), 165-176.
87. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems* (pp. 1097-1105).
88. Acharya, U. R., Fujita, H., Oh, S. L., Raghavendra, U., Tan, J. H., Adam, M., Gertych, A., & Hagiwara, Y. (2018). Automated identification of shockable and non-shockable life-threatening ventricular arrhythmias using convolutional neural network. *Future Generation Computer Systems*, 79, 952-959.
89. Acharya, U. R., Fujita, H., Lih, O. S., Adam, M., Tan, J. H., & Chua, C. K. (2017). Automated detection of coronary artery disease using different durations of ECG segments with convolutional neural network. *Knowledge-Based Systems*, 132, 62-71.
90. Tan, J. H., Hagiwara, Y., Pang, W., Lim, I., Oh, S. L., Adam, M., Tan, R.S., Chen, M., & Acharya, U. R. (2018). Application of stacked convolutional and long short-term memory network for accurate identification of CAD ECG signals. *Computers in biology and medicine*, 94, 19-26.