

Article

Automatic ECG Diagnosis Using Convolutional Neural Network

Roberta Avanzato and Francesco Beritelli *

Department of Electrical, Electronic and Computer Engineering, University of Catania, Catania 95125, Italy

* Correspondence: francesco.beritelli@dieei.unict.it; Tel: +39-095-7382367

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Abstract: Cardiovascular disease (CVD) is the most common class of chronic and life-threatening diseases, therefore considered to be one of the main causes of mortality. The proposed new neural architecture based on the recent popularity of Convolutional Neural Networks (CNN) is a solution for the development of automatic heart disease diagnosis systems using electrocardiogram (ECG) signals. More specifically, ECG signals are passed directly to a properly trained CNN network. The database consists of more than 4000 ECG signal instances extracted from outpatient ECG examinations obtained from 47 subjects: 25 males and 22 females. The confusion matrix derived from the testing dataset indicates 99% accuracy for the "Normal" class. For the "Atrial Premature Beat" class, ECG segments are correctly classified 100% of the time. Finally, for the "Premature Ventricular Contraction" class, ECG segments are correctly classified 96% of the time. In total, there is an average classification accuracy of 98.33%. The sensitivity, SNS, and the specificity, SPC, are, respectively, 98.33 % and 98.35 %. The new approach based on deep learning, and, in particular, on a CNN network, guarantees excellent performance in automatic recognition, and, therefore, prevention, of cardiovascular diseases.

Keywords: ECG signal detection; cardiovascular diseases; convolutional neural network (CNN); myocardial infarction (MI)

1. Introduction

For many years, doctors have been aware that cardiovascular diseases constitute a class of diseases considered to be one of the main causes of mortality [1]. Cardiovascular diseases occur in the form of "Myocardial Infarction" (MI). Myocardial infarction, commonly referred to as "heart attack", stands for the failure of heart muscles to contract for a fairly long period of time. Using appropriate treatment within an hour of the start of the heart attack the mortality risk of the person who suffers from a heart attack in progress can be reduced.

When a heart condition occurs, the first diagnostic check consists of an electrocardiogram (ECG), which therefore is the main diagnostic tool for Cardiovascular Disease (CVD). The electrocardiograph detects the electrical activity of the heart during the test time, which is then represented on a graphic diagram that reflects cyclical electrophysiological events in the cardiac muscle [2]. By conducting careful analysis of the ECG trace, doctors can diagnose a probable myocardial infarction. It is important, however, to underline that the sensitivity and specificity of manual detection of acute myocardial infarction are 91% and 51%, respectively [3].

Developing a computer-aided system to automatically detect MI would help the cardiologists make better decisions. Hence, lately various studies have been conducted on automatic MI detection.

Given the nonlinearity of the heart anomaly classification, techniques based on neural networks have recently been adopted. In a precedent study, the authors, proposed a training technique based

on a Radial Basis Probabilistic Neural Network (RBPNN) in order to offer an efficient solution in the diagnosis of cardiovascular illness [4]. The proposed method has been tested for ECG analysis and the detection of abnormal heartbeats that have been classified by the network in the related pathologies.

Recently, authors have successfully experimented with the newest and most innovative Neural Network (NN) models [5–6], and, more specifically, machine and deep learning techniques, such as the Convolutional Neural Networks (CNN) and audio biometrics techniques [7–9]. CNN have been utilized in arrhythmia detection, coronary artery disease detection, beats classification [10–12]. A deep belief network has been used to classify signal quality in ECG [13].

Some researchers have implemented an 11 layers CNN to detect MI [14]. The authors have demonstrated the use of a shallow convolutional neural network only focusing on inferior myocardial infarction. This network benefits from the use of varying filter sizes in the same convolution layer which allows it to learn features from signal regions of varying length.

In [15] the authors propose a classification system of cardiovascular diseases using the MLP network and the CNN network. In particular, they compare the results obtained by both models, using the same data set but different classes. There are two classes used in the MLP network: "Arrhythmias" and "Normal", while those used for 4–layer CNN are nine classes. ECG data used for the training / validation and test dataset was downloaded from PhysioBank.com and kaggle.com. This study shows low performance both using the MLP network and the CNN network, i.e. 88.7% and 83.5%, respectively.

There are many other studies that deal with the classification of heart disease via the ECG signal using deep learning algorithms based on Convolutional Neural Networks. Table 1 shows the list of the main techniques comparing the learning models used, the parameters of CNN implemented and the obtained performance.

Table 1. Main techniques for classifying ECG signals based on the use of CNN networks

Researcher	Preprocessing	Database	Classes	Model	Accuracy
Acharya et al. [14]	R – Peaks	MIT-BIH arrhythmia	2	1-D CNN, 11 Layers	95.22 %
Savalia et al. [15]	-	MIT-BIH arrhythmia and Keggar	2 (MLP) 9 (CNN)	1-D CNN, 5 Layers	88.7 %
Zubair et al. [16]	-	MIT-BIH arrhythmia	5	1-D CNN, 4 Layers	92.7 %
Li et al. [17]	Wavelet transform	MIT-BIH arrhythmia	5	1-D CNN, 6 Layers	97.5 %
Baloglu et al. [18]	Wavelet transform	MIT-BIH arrhythmia	12 lead ECG	1 – D CNN, 10 Layers	99.8 %
Proposed Method	-	MIT-BIH arrhythmia	3	1-D CNN, 5 Layers	98.33 %

Many other papers extract functionality from the PQRST complex and take advantage of machine learning algorithms based on other techniques.

In [19] the authors use rough sets (RS) and quantum neural network (QNN) to recognize electrocardiogram (ECG) signals. For feature extraction (Peaks-P, Q, R, S and T waves), after normalization of signals, the wavelet transform (WT) is used. Then the attribute reduction of RS is applied as preprocessor so that redundant attributes and conflicting objects can be deleted from the decision making table but retain efficient information lossless. After that, the classification modeling and forecasting test based on QNN is trained using a gradient descent method; the accuracy of this systems is 91.7%.

In [20] RR interval is calculated using the recordings from MIT-BIH arrhythmia database. MLPNN and SVM classifiers are compared in this paper. Results show that MLPNN is good for testing performance while SVM shows good training performance.

In [21] the authors propose a survey on the classification of ECG signals based on machine learning techniques other than CNN.

Table 1 of the study highlights the ECG features, while table 2 details the ECG classification including the number of features, feature names, pre-processing techniques, database, modeling techniques, performance measures used, and accuracy achieved in each paper.

This paper proposes a low-complexity solution for automatic heart disease recognition based on the direct application of a CNN-based classification network to ECG signals, thus bypassing any possible heart disease ECG signals from the time domain to other domains (e.g. frequency domain as MFCC, Wavelet, etc.). This paper evaluates the performance of a classifier in the following three classes: "Normal", "Atrial Premature Beat" and "Premature Ventricular Contraction". The obtained performances are remarkable.

2. ECG Signal and Dataset

From a graphic or numerical point of view, electrocardiogram (ECG) represents the electrical activity of the heart during its operation. The most important elements of an ECG waveform, which repeats for each cardiac cycle, are shown in Figure 1.

ECG is carried out to provide information about different heart diseases that a person can suffer from [22], in order to guarantee effective therapy.

According to international conventions, the specific points that are identified in the trace of an electrocardiogram are labeled with the letters P, Q, R, S, T, and, in particular, are the following:

- P wave: the first wave that occurs in the ECG cycle, a small deflection that represents Atrial depolarization or most commonly called "Atrial Contraction";
- T wave: represents the depolarization of ventricles or most commonly called "Ventricular Relaxation";
- Q, R and S waves: together, these waves form the so-called QRS complex. The QRS complex represents the contraction of the ventricles or, technically speaking, the depolarization complex of the ventricles. In particular, the Q wave represents the depolarization of the interventricular septum, the R wave reflects the depolarization of the main mass of the ventricles, and the S wave is the final depolarization of the ventricles at the base of the heart.

Taken together, the P, Q, R, S and T waves make up the so-called PQRST complex. Cardiologists denote the interval between two PQRST complexes by the term "R-R interval", which corresponds to a cardiac cycle.

Other parameters, which have been extensively used to make medical diagnoses using the ECG trace, are:

- PR interval or PQ interval: the PR interval is a stretch formed by the P wave and the PR segment (rectilinear stretch) that begins with the P wave, that is, during the first deflection, and ends at the QRS complex. This interval indicates the time that the depolarization wave takes propagating from the atrial sinus node along the part of the electrical conduction system of the heart present on the myocardium;
- ST segment, i.e. the time between the end of QRS complex and the start of the T wave;
- QT interval, i.e. the time between the beginning of the QRS complex and the end of the T wave, which is the electrocardiographic manifestation of ventricular depolarization and repolarization [23].

When an ECG is performed on a patient suffering from a heart disease, the diagram outlines a different waveform from that shown in Figure 1. For example, the QT interval may be longer than normal, indicating that the patient may be suffering from a ventricular arrhythmia; the ST segment may have an elevation, which may be associated with myocardial infarction [24 - 25].

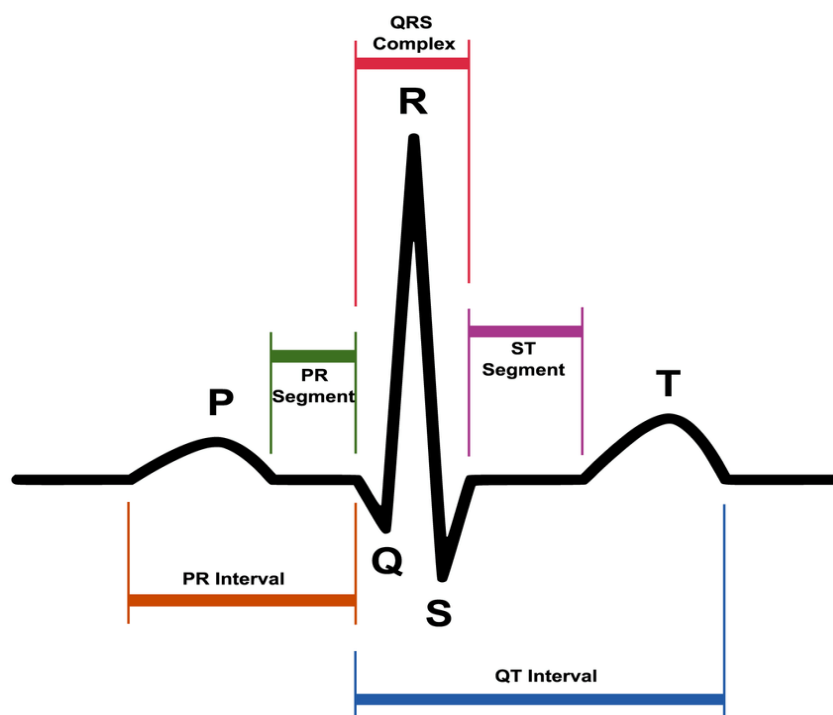


Figure 1. A typical ECG waveform and its characteristic patterns (P and T waves, PR and ST segments, PR and QT intervals, as well as the QRS complex).

One of the most commonly used databases on the field is PhysioNet [26, 27], in particular, the MIT-BIH Arrhythmia Database was used in this study, as shown in Table 1. A large collection of recorded physiologic signals available under the ODC Public Domain Dedication and License v1.0 [28].

The PhysioNet database is composed of 48 ECG recordings of two-channel ambulatory, each 30 minutes long, associated with different clinical pathologies (e.g. ventricular and supraventricular arrhythmia, ventricular tachyarrhythmia, atrial fibrillation, etc.).

The database contains ECG recordings from 47 subjects: 25 males aged between 32 and 89 years and 22 females aged between 23 and 89 years. Twenty-three recordings were chosen at random from a set of 4000 24-hour ambulatory ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample. The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range.

Cardiologists independently annotated each recording; disagreements were resolved to obtain the computer-readable reference annotations for each beat (approximately 110,000 annotations in all) included in the database.

The database is made up of three classes:

- Normal;
- Atrial premature beat;
- Premature ventricular contraction.

Figure 2 shows the differences in the ECG wave between the normal beat, the premature atrial beat and the premature ventricular contraction. The first graph of Figure 2 shows the ECG wave of a normal beat, i.e. a heartbeat not affected by pathologies. This graph can be traced back to the "ideal" one in Figure 1. The second graph shows the ECG wave affected by a premature atrial beat or premature atrial contraction (PAC).

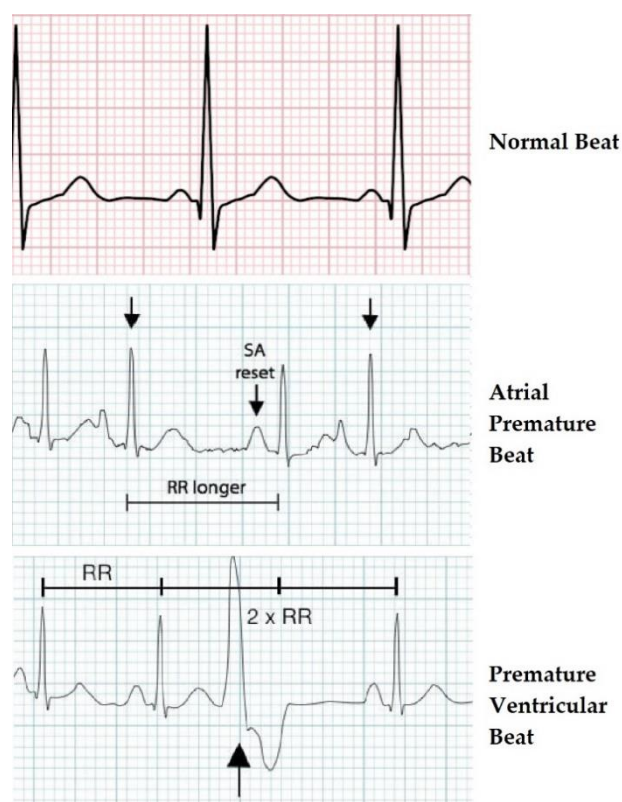


Figure 2. ECG waveforms of the three heartbeat classes.

It is a common cardiac dysrhythmia characterized by premature heartbeats originating in the atria. While the sinoatrial node typically regulates the heartbeat during normal sinus rhythm, PACs occur when another region of the atria depolarizes before the sinoatrial node and thus triggers a premature heartbeat. Therefore, the difference from a normal ECG wave lies in the PR segment that is formed prematurely. In Figure 2, “RR longer” stands for the time between QRS complexes, while “SA reset” indicates the reformation of electrical impulse beginning in the sinoatrial (SA) node and propagating to the atrioventricular (AV) node.

The third graph shows an ECG wave affected by premature ventricular contraction (PVC).

It is a relatively common event where the heartbeat is initiated in the ventricles rather than by the sinoatrial node.

From what has been said, it is clear now how an automatic diagnosis system must perform in detecting these differences in duration and shape of the waves and segments that make up the PQRST complex.

The used dataset was not recorded by the authors but originates from 2001 study by Moody et al. [26]. Therefore, the authors are not responsible for the applied data collection procedure. Original authors of the database state that all ethical requirements have been followed. Moreover, the database is available online for an extended period now and has been used extensively in many recent publications (see Table 1). Finally, all records in the database have been anonymised.

3. ECG Diseases Classification based on CNN

3.1. CNN General Characteristics and Architecture Adopted

Convolutional Neural Networks, or CNNs, are a specialized kind of neural network for processing data that has a known grid-like topology. Examples include time-series data, which may be considered as a 1-D grid taking samples at regular time intervals, and image data, which may be considered as a 2-D grid of pixels.

The general characteristics and architecture of this network are described in [29], where the only difference is the sample rate used. In this study and also in [30] the sample rate is 44.1 kHz instead of 8 kHz.

The deep convolutional neural network is mainly composed of:

1. 1D convolution layers;
2. Batch normalization layers;
3. RELU layers;
4. Pooling layers;
5. Softmax.

Only in the first convolution a convolutional kernel composed of 80 elements is used, with respect to the subsequent convolution layers where it is set to 3, with the aim of reducing the computational cost.

After each convolution, Batch normalization is carried out to avoid the explosion of the parameters and the phenomenon of "vanishing gradients". Batch normalization allows training deep networks and is applied after each convolutional layer and before performing the ReLU (rectified linear activation function). The level of pooling in CNN, placed before RELU, reduces the problem of data overfitting by the network, taking the input size by half the actual input.

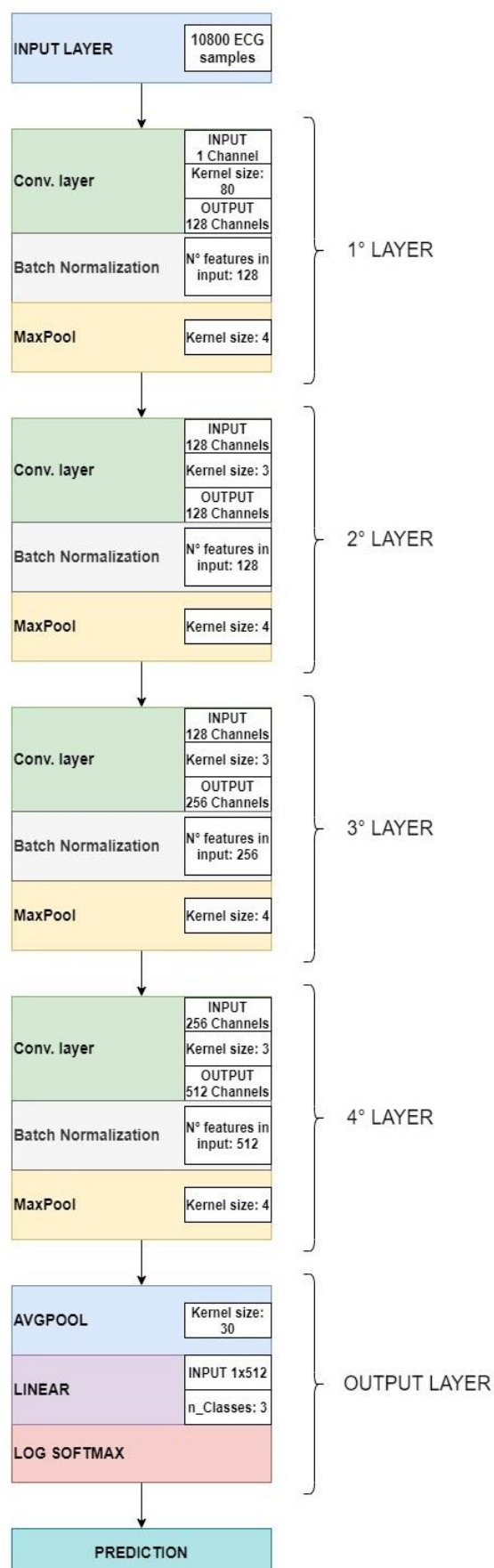
Unlike the classic CNN, which use fully connected neurons as their output layer, this network performs a single AvgPool and then a LogSoftMax softmax followed by a natural logarithm log (softmax (x)).

The structure of the proposed network is illustrated in Table 2 below.

Table 2. The structure of the proposed network.

INPUT	vectors of 10800 ECG samples		
LAYER 1	Conv1D (1, 128, 80, 4): - input 1 channels - output 128 channels - kernel_size 80 - stride 4	BatchNorm1D (128): - N_features: 128	MaxPool1D: - kernel_size 4
LAYER 2	Conv1D (128, 128, 3): - input 128 channels - output 128 channels - kernel_size 4	BatchNorm1D (128): - N_features: 128	MaxPool1D: - kernel_size 4
LAYER 3	Conv1D (128, 256, 3): - input 128 channels - output 256 channels - kernel_size 4	BatchNorm1D (256): - N_features: 256	MaxPool1D: - kernel_size 4
LAYER 4	Conv1D (256, 512, 3): - input 256 channels - output 512 channels - kernel_size 4	BatchNorm1D (512): - N_features: 512	MaxPool1D: - kernel_size 4
OUTPUT LAYER	AvgPool1D (30): - kernel_size 30	Linear (512, num_classes): - input 1 x 512 - output num_classes: 3	Log Softmax

Figure 3 shows the structure of the proposed convolutional neural network.



Deep neural networks can both extract and classify the representation of features, rather than perform these two functions separately. After being processed, the ECG recording is sent to the CNN network as an input, for the classification of pathologies by means of the ECG signal in three classes: normal, atrial premature beat and premature ventricular contraction; based on convolutional neural networks (CNN).

3.2. Training/Validation and Testing Dataset

Neural network input consists of 30-second segments where every second of ECG recording is equivalent to 360 samples, for a total of 10800 samples.

So, the dataset presents the following classes:

- "Normal" class, containing 1421 ECG segments.
- "Premature Ventricular Contraction" class, containing 335 ECG segments;
- "Atrial Premature Beat" class, containing 133 ECG segments;

This dataset was subsequently divided into two different datasets, see Figure 4 below:

- Training/Validation set, consisting of 995 segments for the "Normal" class, 234 segments for the "Premature Ventricular Contraction" class and 93 segments for the "Atrial Premature Beat" class. 70 % of this set was used for the training and the other 30% was used for the testing;
- Testing set, consisting of 426 segments for the "Normal" class, 101 segments for the "Premature Ventricular Contraction" class and 40 segments for the "Atrial Premature Beat" class.

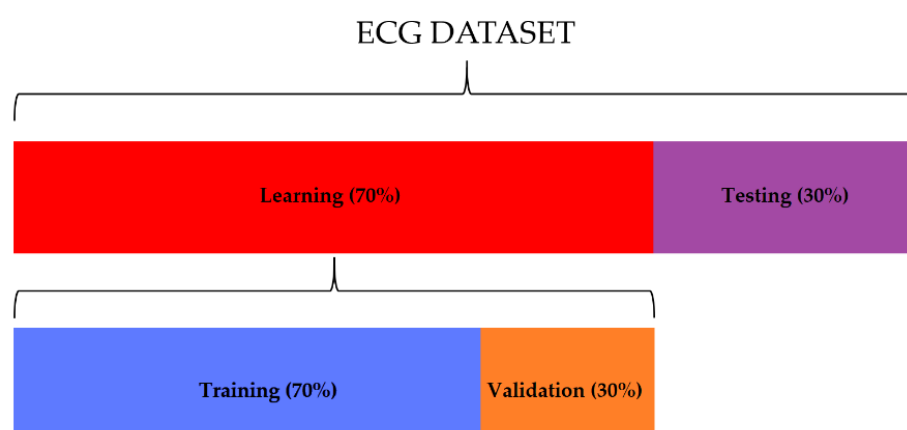


Figure 4. The distribution of ECG segments used for learning (70%) and testing (30%). 30% of the learning dataset was used for the validation of the network.

At first, the network was trained by entering the data relating to the "Training set" as input, then it was validated using the "Validation set", in order to evaluate the performance of the neural network (the percentage of loss and accuracy). Finally, the "Testing set" was applied to validate and verify, through the accuracy estimate, the robustness of the neural network to data external to the training / validation set.

4. Methods

As previously stated, for the purposes of performance evaluation, the proposed study uses the PhysioNet database, typically employed as a reference database in the automatic classification of cardiac pathologies based on ECG signals. From this dataset, the data relating to learning and testing of the neural network was obtained for the assessment of classification accuracy. Accuracy indicates that the network performs great classification of the two classes related to heart disease ("Atrial Premature Beat" and "Premature Ventricular Contraction") and the one relating to the state of good health. Based on the results obtained from the confusion matrix, it is possible to evaluate the proposed method, applying the statistical classification functions [31]: *sensitivity*, also known as True

Positive Ratio (TPR), *specificity*, also known as True Negative Ratio (TNR), *Fall - Out*, also known as False Positive Ratio (FPR) and the measure of the test accuracy.

Hence, it is possible to define the meaning of each statistical classification parameter described above: sensitivity indicates the percentage of ECG recordings belonging to a specific category and correctly classified in that category; specificity measures how often the classifier can classify the ECG recordings not belonging to that category; Fall – Out indicates that ECG recordings are considered to belong to a specific category, but in reality they are not part of it; false discovery ratio indicates that ECG recordings are not considered to belong to a specific category, but that in reality they are part of it; F1 Score takes into account precision and recovery of the test, where precision is the number of true positives (TP) divided by the number of all positive results, i.e. true positives (TP) plus false positives (FP); while recovery is the number of true positives (TP) divided by the number of all tests that should have been positive, that is, true positives (TP) plus false negatives (FN).

The following equations relate to the classification functions previously described.

$$TPR = \frac{TP}{TP + FN}, \quad (1)$$

$$TNR = \frac{TN}{FP + TN}, \quad (2)$$

$$FPR = 1 - TNR, \quad (3)$$

$$FDR = \frac{FP}{FP + TP}, \quad (4)$$

$$F_1 = \frac{2TP}{2TP + FP + FN}. \quad (5)$$

5. Performance Analysis

5.1. Test results

In this section, the results of training and subsequent validation of the neural network are presented and discussed. Figures 5a and Figure 5b represent the progress of the training and validation loss and the progress of the training and validation accuracy, respectively. As the graphs show, after 100 epochs training and validation losses stabilize at a value close to zero (Figure 5a), while training and validation accuracy stabilizes at 100%.

Such data are very encouraging, as it is understood that there is a good percentage of accuracy in the classification of the three classes described above.

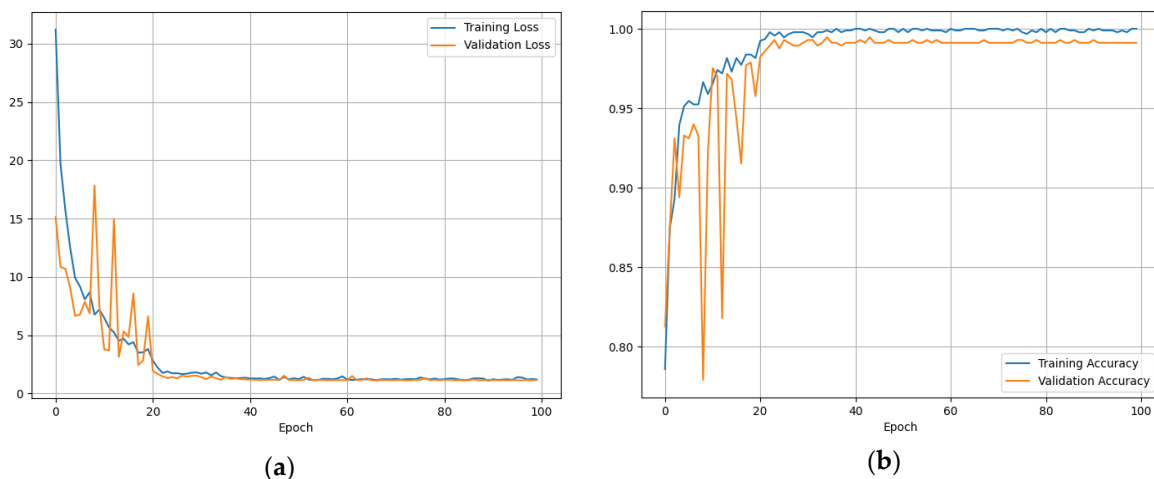


Figure 5. (a) Training and validation losses (b) Training and validation accuracy.

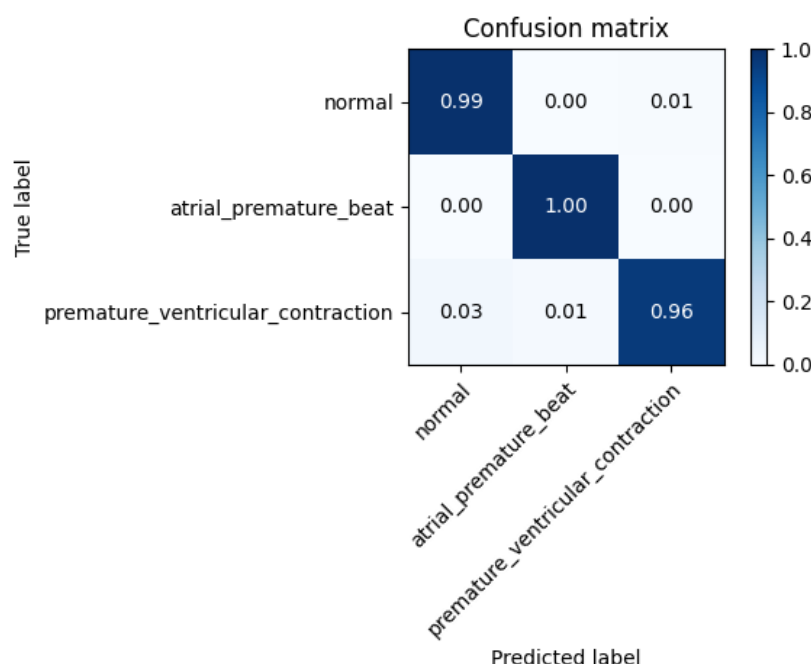


Figure 6. Confusion Matrix for “Testing set”.

In order to evaluate the performance of the CNN network with ECG sequences external to the training dataset, the accuracy obtained with the “Testing set” is assessed. Figure 6 shows the relative confusion matrix.

The matrix highlights an average classification accuracy level of 98.33 %.

The results obtained in terms of the statistical parameters described in section 5 are shown in Table 3.

Table 3. The table reports the overall values of accuracy TPR, TNR, TPR, TDR and F1 score.

α	Class	TPR	TNR	FPR	FDR	F1 Score
1	Normal	99.0 %	97.1 %	2.9 %	1 %	98.0 %
2	Atrial Premature Beat	100 %	99.0 %	1.0 %	0 %	99.5 %
3	Premature Ventricular Contraction	96.0 %	98.96 %	1.04 %	4 %	97.5 %
Mean Accuracy		98.33 %	98.35 %	1.65 %	1.66 %	98.33 %

5.2. Cross validation analysis

In this paragraph we will describe the method used for the cross validation of data, which has been used to obtain reliable estimates of the generalization error of the model, or how the CNN network behaves on data other than learning data.

In particular, K-fold [32] cross validation was used in this study, which involves randomly dividing the training dataset into k parts without reintegration: the K-1 parts are used for training the model and a part is used for testing. This procedure is repeated k times so as to obtain k models and performance estimates.

Subsequently, the average performance of the models is calculated on the basis of the different independent subdivisions to obtain an estimate of the performance that is less sensitive to the partitioning of the training data.

Since k-fold cross validation is a resampling without reintegration technique, the advantage of this approach is that each sample point will be part of the training and test datasets only once, which provides a lower variance estimate of the template performance.

For this study, the training dataset is divided into ten parts, $K = 10$, and during the ten iterations, nine parts are used for training and one part is used as a test set for model evaluation. In addition, the estimated performance E_i (for example, the accuracy of the classification) of each part is then used to calculate the average estimated performance E of the model. Figure 7 depicts the concept of the k-fold cross validation technique. The average accuracy and standard deviation for the model used in this study is $96.8 \pm 1.2\%$.

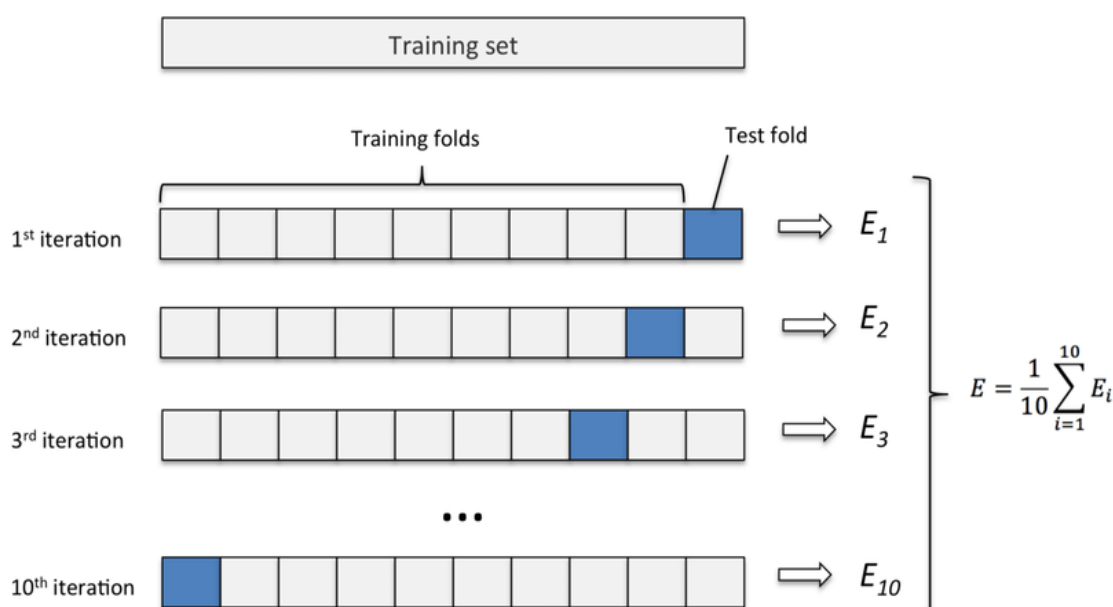


Figure 7. K-fold cross validation method with subdivision of the training set into $k = 10$ parts

6. Discussion

Table 4 shows a comparison between our method and other methods in terms of feature extraction (FE), model used, system's accuracy, and the statistical classification accuracy.

Hereinafter the differences between this work and the state of the art will be discussed. In [33 - 34] the authors use the extraction of decision tree (DT) and R-Peak (RP) as features and do not apply convolutional neural networks (CNN), but rather the Discrete Wavelet Transformation (DWT) and the Feed-Forward Neural Network (FFNN). The authors claim an average accuracy of 96.56% and 87.66% respectively, while in our study the average accuracy is equal to 98.1 %. This result is higher than the study proposed in [33 - 34].

Compared to the approaches proposed in [5], [14 - 16] and [33 - 34], our method has higher classification performances. As far as the studies proposed in [17 - 18] are concerned, it is evident that they have quite comparable performances, but they use more hidden layers than our study, with a consequent increase in computation costs. In addition, they do a preprocessing of data using wavelet transformation, which implies an additional computational cost. Also from the point of view of the structure of the neural network, in [17], in particular, 5 layers (two convolution layers, two down sampling layers and one full connection layer) plus the output layer formed by Softmax are used for classification, however, we use another structure (previously described), which is more robust to the "vanishing gradients" phenomenon.

In addition, to ensure that the model is correct, we apply the K-fold technique (previously described) for cross validation, obtaining an average accuracy of 96.8% and standard deviation of $\pm 1.2\%$.

Usually, the processing unit implements the automatic disease classification algorithm described above, showing the result of the diagnosis on the display. A possible alternative is to transmit in real-time ECG sequences via data cellular connection (4G dongle) [35 – 36] to a cloud platform, where an automatic ECG diagnosis is implemented in "as a service" mode. The robustness to the IP packet loss, typical of a 4G data connection, was verified by sending the test database several times from a transmitter to a 4G data receiver. The classification results confirm the same values obtained in the case of processing on local board.

Table 4. Comparison between the proposed method and those previously studied

Method	FE	Model	ACC	TPR	TNR	FPR	FDR
Sridhar et al. [33]	DT	DWT	96.56%	90.87%	98.45%	9.13 %	1.55 %
Ranjan et al. [34]	RP	FFNN	87.66%	94.04%	76.21%	5.96 %	23.79 %
Acharya et al. [14]	RP	11 – Layer CNN	95.22%	95.49%	94.19%	-	-
Beritelli et al. [4]	-	PNN	96.53%	93.1%	100%	-	-
Savalia et al ^{*,+} . [15]	-	MLP / 5 – Layer CNN	88.7% / 83.5%	-	-	-	-
Zubair et al. [16]	-	4 – Layer CNN	92.7 %	-	-	-	-
Li et al. [17]	Wavelet transform	6 – Layer CNN	97.5 %	-	-	-	-
Baloglu et al. [18]	Wavelet transform	10 – Layer CNN	99.8 %	99.5%	-	-	-
Proposed Method	-	5 – Layer CNN	98.33 %	98.33 %	98.35 %	1.65 %	1.66 %

* Different dataset for training/validation and testing

+ Use more cardiovascular diseases classes

7. Conclusions

This paper proposes an automated heart disease recognition technique based on recent and innovative CNN networks. The proposed technique has high accuracy and has low complexity of implementation. This approach harnesses the potential of deep learning to capture the typical characteristics of a given heart disease in the ECG signal domain.

Using the "Validation set", the proposed method yields the following results:

- 98.33 % Mean Accuracy;
- 98.33 % Sensitivity;
- 98.35 % Specificity;
- 1.65 % False Positive Ratio;
- 1.66 % False Negative Ratio.
- 98.33 % F1 Score.

By comparing and contrasting various methods in the "Discussion" section, we can affirm that the method applied in the present paper yields considerably better performances than those of the state of the art.

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