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Extracting Features from ECG and Respiratory Signals for Automatic Supervised Classification of Heartbeat Using Neural Networks

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Abstract: Electrocardiogram (ECG) is today one of the essential pillars of the diagnosis of heart problems. The analysis of this signal and the identification of its parameters is an important step for diagnosis. In this study, we present a new algorithm for ECG signal classification. Respiratory signal simultaneously recorded with the ECG signal will be used to classify each heart beat into two classes (abnormal and normal class) by the extraction of their parameters using various Multi-Layered Perceptron Neural Classifiers (MLPNNs). Principal Component Analysis (PCA) is used to reduce dimensions of input features and improve the performance of the neural classifiers. This algorithm is tested on Apnea-ECG database from the universal MIT PhysioNet. As it will be shown later, the proposed algorithm allows to achieve high classification performances, describes both by sensitivity, specificity and the rate of correct classification parameters.

Key words: ECG signal, respiratory signal, multi-layered perceptron neural classifiers, principal component analysis, Apnea-ECG database

INTRODUCTION

The electrocardiogram ECG, represents the electrical activity of the heart. A typical ECG signal has three important parameters P, QRS, T which characterize the cardiac activity (Fig. 1a). Another wave, called U wave is also present but its importance is not yet identified (Slimane and Reguig, 2008; Slimane and Nait-Ali, 2010). Respiratory signal simultaneously recorded with the ECG signal (Fig. 1b) can be very important in the diagnostic of some cardiac arrhythmia. There have been various approaches proposed in the literature for ECG or Respiratory signal classification such as the use of cross Wavelet Transform (XWT) for the analysis and classification of Electrocardiogram (ECG) signals developed by Banerjee and Mitra (2014). A support vector machines for automated recognition of obstructive sleep apnea syndrome from ECG recordings has been proposed by Khandoker *et al.* (2009). Longa *et al.* (2014) have proposed an analyzing respiratory effort amplitude for automated sleep stage classification (Longa *et al.*, 2014). In this study, the both signals (ECG and respiratory signals) will be used to classify each heart beat into two classes (abnormal and normal class) by the extraction of their parameters using various Multi-Layered Perceptron Neural Classifiers (MLPNNs). In the research, we found that the QRS complex has a significant relationship with the respiratory rhythm especially in pathological cases. This relation will be used to improve the performance of our classifier. Principal Component Analysis (PCA) is used to reduce the input vector. To evaluate performance of the different multi-layered perceptron neural classifiers, Sensitivity (SE), Specificity (SP) and Correct Classification (CC) are calculated. The proposed classification algorithm is tested on Apnea-ECG database from the universal MIT PhysioNet. As we will show later, very promising results are obtained (Fig. 1).

Review of the Artificial Neural Networks (ANN): The field of artificial neural networks tries to simulate and to fabricate networks and devices in the spirit of neurobiology to solve useful computational problems of the kind that biology does effortlessly (Hopfield, 1988). There have been different models of neural proposed in the literature. The distinction between them is depending to the patterns of connection between the units and the propagation of data. Multi-Layer Perceptron (MLP) is the most commonly used neural network architecture and frequently used in biomedical signal processing (Lippmann, 1987). Multi-layer perceptrons are feed-forward nets with input, hidden and output layers (Fig. 2).

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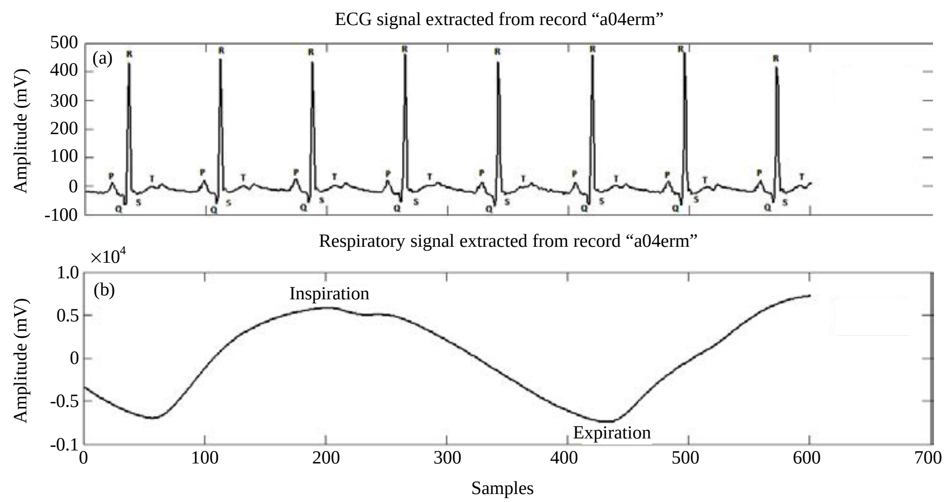


Fig. 1: Respiratory signal simultaneously recorded with the ECG signal

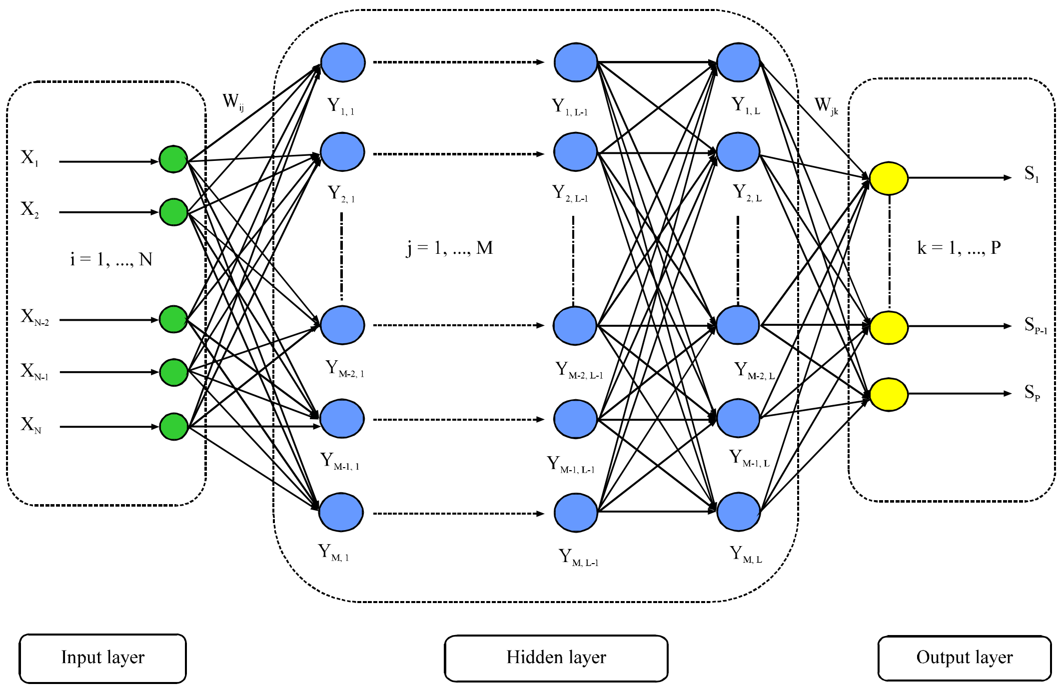


Fig. 2: General structure of a layered artificial neural network

MATERIALS AND METHODS

Description of the implemented method: Figure 3 shows a block diagram of the automatic supervised classification algorithm. This algorithm requires the following stages: signal processing step, features extraction, data compression and finally training and classification operation. The proposed detection algorithm is evaluated on some reference ECG-respiratory signals available from MIT PhysioNet Apnea-ECG database in PhysioBank (Penzel *et al*., 2000). The Apnea-ECG database consists of 70 ECG recordings sampled at 100 Hz; the lengths of the recordings vary from 7-10 h long with appending annotations acquired from a study of simultaneously recorded respiration signals which are included for 8 of the recordings. Only of them include respiration signals (age: 43.3±8.3 years, 7 M and 1F).

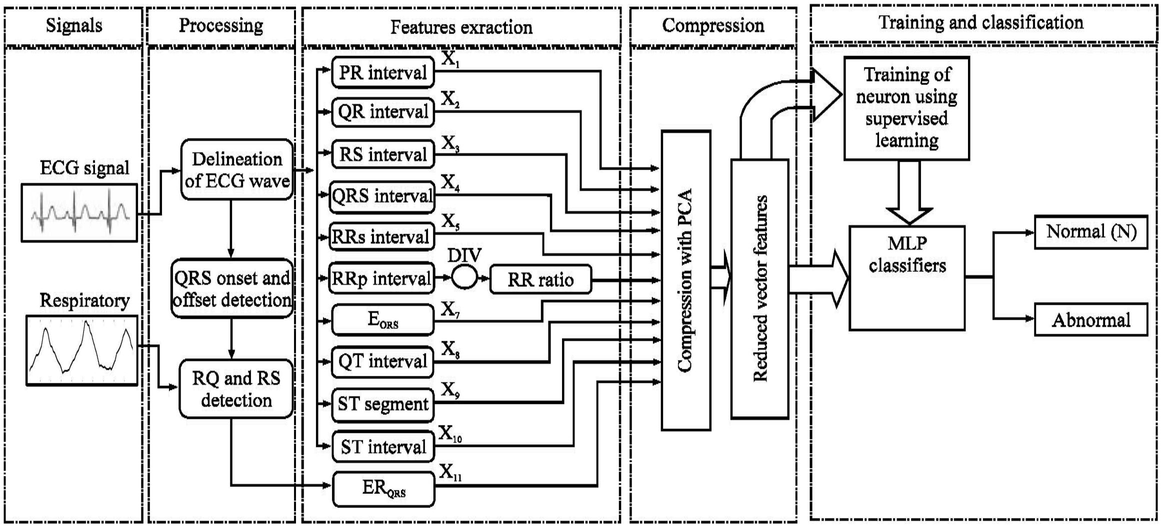


Fig. 3: Block diagram of our Automatic Supervised Classification algorithm

Signal processing step

Delineation of ECG wave: The ECG signal typically consists of three important waves known as the P, QRS and T waves. Various time intervals defined by the onsets and ends of these waves are important in electrocardiographic diagnosis. The most important of these intervals are the RR interval, the PQ interval, the QRS duration, the ST segment and the QT interval (Fig. 4).

P wave, QRS complex, T wave and ECG intervals measurement were defined by using an algorithm previously reported in detail (Slimane and Reguig, 2008; Zine-Eddine *et al*., 2010; Bachir and Slimane, 2013). It includes the following basic steps: a high-pass filter, signal empirical mode decomposition, QRS detection, QRS onset, T wave-end and P wave definition.

R_Q-position and R_S-position detection: In the next stage, we define R_Q-position and R_S-position by projection of the Q point and S point on the respiratory signal (Fig. 5).

Energy measurement of QRS complexes and respiratory signal: The energy of QRS complex is defined as:

$$E_{QRS} = \sum_{n=Q_p}^{S_p} |ECG(n)|^2 \tag{1}$$

where, Q_p and S_p are respectively the beginning and the end of the QRS complex. The energy of respiratory signal is defined as:

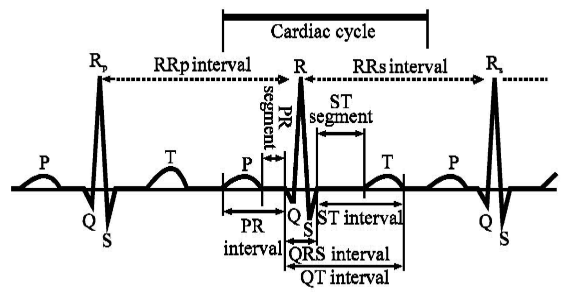


Fig. 4: The most significant intervals of the ECG signal

$$ER_{QRS} = \sum_{n=R_Q}^{R_S} |Resp(n)|^2 \tag{2}$$

where, R_Q and R_S are respectively the projection of the Q point and S point on the respiratory signal noted Resp.

Feature extraction: For each ECG heartbeat and the corresponding respiratory party, a feature vector is extracted that represents some features of signals. In the research, both temporal and energy are used for classification process. These features are described in Table 1. In total, we used 11 features for the experiments of feature selection. The concatenation of vectors X_1-X_{11} gives us one vector X to be used as input of the classifier such as:

$$[X] = [X_1, X_2, ..., X_{11}] \tag{3}$$

We obtain a simple expression for $[X_i]$ i = 1, ..., 11:

$$[X_i] = (X_i[0], X_i[1], X_i[2], ..., X_i[L-1])^T \quad (4)$$

where, L is the number of QRS complex for each treated portion. So, we can see that the length of the vector [X] is 11L.

PCA-based feature vector compression: Principal Component Analysis (PCA) is extensively used in feature extraction to reduce the dimensionality of the original data by a linear transformation. PCA extracts dominant features (principal components) from a set of multivariate data. PCA is also used for ECG data compression (Chawla, 2009).

In the research, Principal Component Analysis (PCA) is applied not to the ECG or respiratory signals but to the feature vector [X]. It reduces the size of the vector [X] in order to improve the performance of our neural classifier.

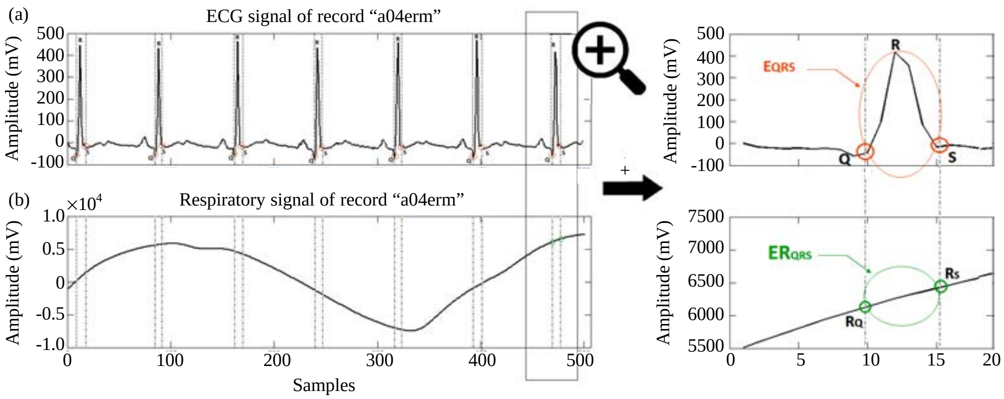
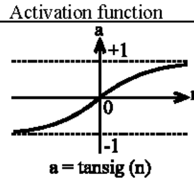
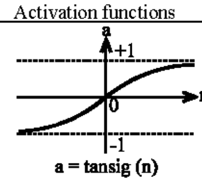
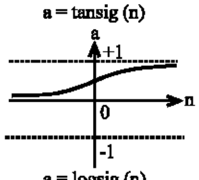
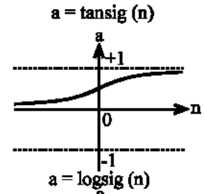
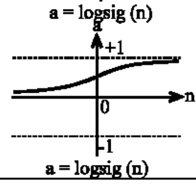
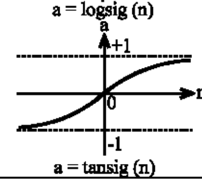


Fig. 5: Energy measurement of QRS complexes and respiratory signal

Table 1: Features extracted from ECG and respiratory signals with their assigned vectors

Designations	Description	Assigned vectors
R-R interval duration	Interval between two successive QRS	X_1
Q-R interval duration	Interval between R peak and the beginning of QRS complex	X_2
RS interval duration	Interval between the end of QRS complex and the peak R	X_3
QRS complex duration	Interval between the end and the beginning of the QRS complex	X_4
RR_S interval duration	Interval between the current R peak and the following R peak	X_5
RR ratio	$RR_{ratio} = RR_S/RR_p$	X_6
E_{QRS}	Energy of QRS complex	X_7
QT interval duration	Interval between T-end and the beginning of QRS complex	X_8
ST segment duration	Interval between the beginning of T wave and the end of QRS complex	X_9
ST interval duration	Interval between T-end and the end of QRS complex	X_{10}
ER_{QRS}	Energy of respiratory signal	X_{11}

Table 2: The topology of the different MLPNNs used

MLP	Hidden layers	Activation function	Output layers	Activation functions
MLP1 MLPR1	6		1	
MLP2 MLPR2				
MLP3 MLPR3				

Training and classification: In order to classify the heart beat into normal and abnormal beats, various Multi-Layered Perceptron Neural Networks (MLPNNs) are used namely: MLP1, MLPR1, MLP2, MLPR2, MLP3 and MLPR3. In Table 2, the architecture of the different MLPs used are be presented. In MLP structure, the features will be extracted only in ECG signal. For MLPR, features are extracted from both the ECG signal and the respiratory signal. As we can see in Table 2, the difference between MLP1, MLP2 and MLP3 is the choice of the activation function in the hidden units. Same thing for the MLPR1, MLPR2 and MLPR3 topologies. The six proposed MLP neural networks will be used to classify each heart beat into two classes (abnormal and normal class). The three-layer artificial neural networks are configured as follows: one input layer, 6 hidden layers (L = 6) and one output layer. Each hidden layer contains M neurons (Fig. 2). Fifteen neurons for each hidden layer are used in MLP1 and MLPR1 topologies, ten neurons in MLP2 and MLPR2 and fifteen neurons in MLP3 and MLPR3. Table 2 summarizes the different topologies of MLP used.

RESULTS AND DISCUSSION

A comparative study is made between the six MLPs topologies presented in this research. The proposed classification algorithm is tested on Apnea-ECG database from the universal MIT PhysioNet. All of the programs were written in MATLAB environment under a Pentium I5 PC platform (2.5 GHz, 4 Go RAM).

As we have presented in the precedent section. The first input data used in the input of classifiers (MLPR1-MLPR3) is a set of 11 element vectors X_i, representing the ECG features and respiratory energy. The second input data used in the input classifiers (MLP1-MLP3) is a set of 10 element vectors X_i, representing only the features of the ECG signal.

The different neuronal networks were trained to obtain the final weights and biases. The performance parameters during training of the networks are shown in Fig. 6 and 7.

Three statistical indicators, Correct Classification (CC), Sensitivity (Se) and Specificity (Sp) have been used to evaluate the performance of the different MLPNNs classification system. The sensitivity S_e and the specificity S_p are normally computed by:

$$SE = \frac{TP}{TP+FN} \tag{5}$$

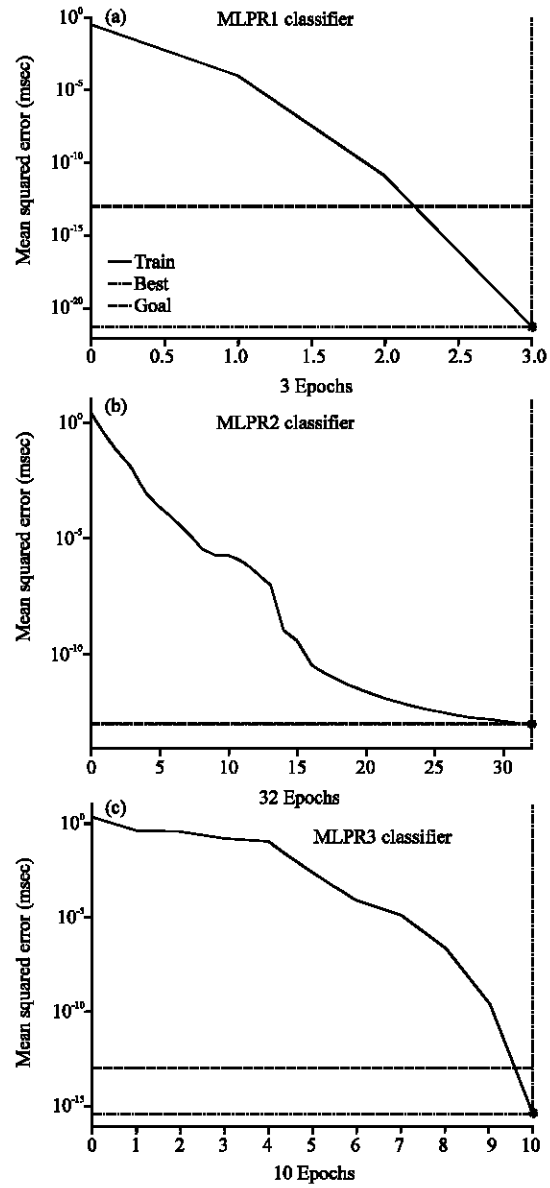


Fig. 6: Training performance of MLPR classifiers: a) best training performance is 4.9932e-22 at epoch 3; b) best training performance is 9.4158e-14 at epoch 32 and c) best training performance is 3.4362e-16 at epoch 10

$$SP = \frac{TN}{TN+FP} \tag{6}$$

Correct Classification (CC) is defined as follows:

$$CC = \frac{TN+TP}{TP+TN+FN+FP} \tag{7}$$

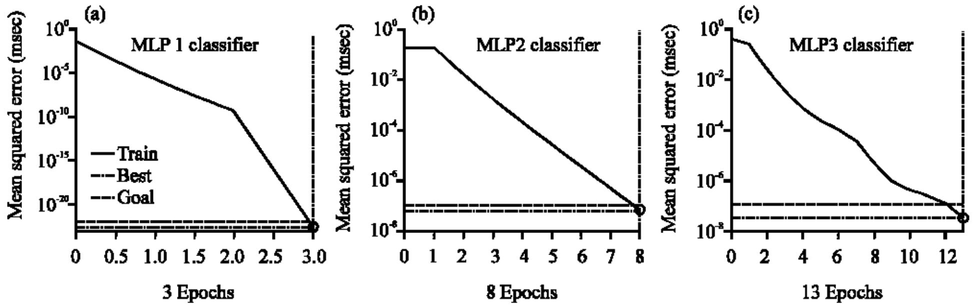


Fig. 7: Training performance of MLP classifiers: a) best training performance is 2.338e-23 at epoch 3; b) best training performance is 6.0026e-08 at epoch 8 and c) best training performance is 2.8422e-08 at epoch 13

Table 3: Performance analysis of the MLPR classifiers

Record/ Classifiers	MLPR1 (%) Accuracy	Sensitivity	Specificity	MLPR2 (%) Accuracy	Sensitivity	Specificity	MLPR3 (%) Accuracy	Sensitivity	Specificity
a01erm	98.00	100.00	60.00	98	100.00	60.00	96	97.89	60.00
a02erm	97.00	100.00	40.00	97	100.00	40.00	95	97.89	40.00
a03erm	96.00	100.00	42.85	96	100.00	42.86	96	100.00	55.55
a04erm	98.00	100.00	66.66	98	100.00	66.66	96	98.91	62.50
b01erm	97.00	98.91	75.00	98	98.94	83.33	93	96.63	63.63
c01erm	97.00	98.91	75.00	98	98.92	85.71	95	95.50	90.91
c02erm	95.05	97.80	70.00	98	98.91	87.50	92	95.24	75.00

Table 4: Performance analysis of the MLP classifiers

Record/ classifiers	MLP1 (%) Accuracy	Sensitivity	Specificity	MLP2 (%) Accuracy	Sensitivity	Specificity	MLP3 (%) Accuracy	Sensitivity	Specificity
a01erm	96	100.00	71.43	98	100.00	81.81	96	100.00	73.33
a02erm	95	100.00	64.28	97	100.00	72.72	95	100.00	66.66
a03erm	94	100.00	66.66	97	100.00	78.57	94	100.00	64.70
a04erm	96	100.00	76.47	98	100.00	84.61	96	100.00	76.47
b01erm	95	98.76	78.95	96	97.67	85.71	90	93.10	69.23
c01erm	95	98.76	78.95	96	97.67	85.71	89	92.13	63.63
c02erm	92	97.50	70.00	92	95.29	73.33	87	91.46	66.66

Table 5: Classification accuracy for different MLP topology

Classifieres	Accuracy (%)
MLP1	94.71
MLP2	96.28
MLP3	92.42
MLPR1	96.86
MLPR2	97.57
MLPR3	94.71

Where:

TP = The number of true positive recognized beats
TN = The number of true negative recognized beats
FP = The number of false positive recognized beats
FN = The number of false negative recognized beats

The overall average detection rate is defined as the percentage of recognized beats to the total number of tested beats. Table 3 and 4 summarize the classification performance of the six MLPs topologies presented in this research. Table 5 shows the comparative result of accuracy average of each MLPNN applied on seven different signals.

According to the results illustrated in all tables, among different proposed MLPNNs, it was found that the classifier MLPR2 produced the best classification results performances.

As shown in Table 5 and Fig. 8, the classifiers of type MLPR gives good results compared to the MLP classifier. Also, we can see that MLP2 (CC = 96.28%) provides good classication p erformance comparatively with MLP1 and MLP3 (94.71% for MLP1 and 92.42% for MLP3). Likewise for the MLPR2 topology (CC = 97.57%) where there is a more efficient classification compared to MLPR1 and MLPR3 topologies (96.86% for MLP1 and 94.71% for MLP3). It involves that the right choice of the activation function and data features for each layer affect the recognition rate in the classifiers.

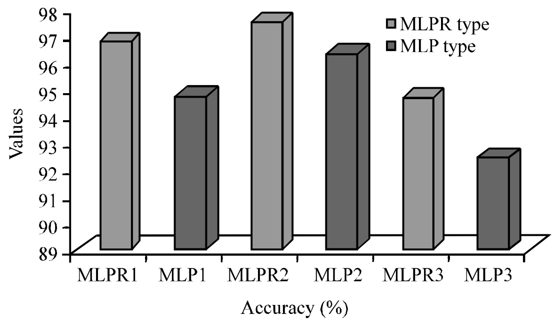


Fig. 8: Histogram of average Correct Classification (CC) for each MLPNN used

CONCLUSION

In this study, a new approach based on neural and energy networks for the automatic classification of ECG signal is applied. As we have seen previously, the proposed scheme uses various stages including, signal processing step, feature extraction, PCA-based feature vector compression, training and classification. The aim is to identify the normal and abnormal beat in ECG signal by using six different multi-layered perceptron neural classifiers namely: MLP1, MLPR1, MLP2, MLPR2, MLP3 and MLPR3. A comparative study was made between the six MLPs topologies presented in this research. The proposed classification algorithm is tested on Apnea-ECG database from the universal MIT PhysioNet. We have shown that the classifier MLPR2 produced the best classification results performances describe both by the sensitivity (S_e), the specificity (S_p) and Correct Classification parameters (CC).

According to the present research, we can conclude that the right choice of the activation function and data features for each layer greatly affects the recognition rate in the classifiers.

For this we believe that the proposed scheme can be served as an effective tool for cardiologists to diagnose heart diseases based on ECG and respiratory signals.

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