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FACULTY OF ENGINEERING, CAIRO UNIVERSITY

MACHINE LEARNING FOR BLOOD PRESSURE CLASSIFICATION USING ONLY THE ECG SIGNAL

A. R. SHABAAN[1] AND A. A. SHARAWI[2]

ABSTRACT

Continuous reading of vital signs in the Intensive Care Unit plays a major role for the physician, which allows him to intervene in a timely manner. Thus, continuous blood pressure measurement remains a difficult task as long as it is based on using a mercury device or other wide varieties of methods. The proposed approach of the current research is based on classifying blood pressure records obtained from the analysis of the Electrocardiogram (ECG) solely using signal processing techniques. The analysis starts with Butterworth filtration of the ECG signal. Following that trend removal and normalization of the signal take place before extracting 27 features. Feature selection is applied to reduce the number of features to the most dominant ones, and as a result the number of features was reduced to 10. The final results point to a high accuracy of 98.18% using a support vector machine (SVM) classifier. Other classifiers like artificial neural networks (ANN) and Naïve Bayes (NB) classifiers were also used but gave lower accuracies of 96.5% and 96.08 %, respectively.

KEYWORDS: SVM classifier, blood pressure, electrocardiogram, heart rate, machine learning, wrapper feature selection.

1. INTRODUCTION

The blood pressure is the pressure caused by the heart to pump blood to all parts of the body. A blood pressure cycle has two phases. The first is the systolic blood pressure phase, representing the pressure during the contraction of the heart. The second one is the diastolic blood pressure phase, representing the pressure while the heart rests [1]. The American Heart Association [2] categorized the blood pressure according Table 1.

[1] Lecturer Assistant, Systems and Biomedical Engineering Department, The Higher Institute of Engineering, El-Shorouk City, Egypt., eng.abd_elrhman@yahoo.com
[2]Associate Professor, Systems and Biomedical Engineering Department, Cairo University, Faculty of Engineering.

Table 1. Blood pressure category and number of representative signals.

Blood pressure category	Systolic (mmHg)	Logic	Diastolic (mmHg)	Number of signals recorded for each category	Category Code
Normal	Less than 120	And	Less than 80	45	N
Elevated	120-129	And	Less than 80	80	E
Hypertension stage1	130-139	Or	80-89	190	H1
Hypertension stage2	140 or higher	Or	90 or higher	388	H2
Hypertension Crisis	180 or higher	Or	120 or higher	12	HC

According to the Egyptian Government, hypertension is one of the major problem diseases worldwide; the rate of the hypertensive population ranges from 20% to 30% of the adult population [3].

In Egypt, 26.3% of adults suffer from hypertension, and only 37% of them know about their disease [4].

Regarding the significance of continuous blood pressure monitoring in Intensive Care Units, the reading of blood pressure is one of the major requirementsthat allows the physicianto intervene in a timely manner [5]. To the best of our knowledge, indirect continuous blood pressure measurement is a subject of research since beginning of the twenty-first century [6-24].

Indirect methods were usedto measure theblood pressure without the need for a cuff,for example by means of the pulse transit time (PTT) and the photo-plethysmo gram (PPG) [6, 7, 11]. Other researchers used the ECG and PPG to estimate blood pressure as indirect methods, however these methodsrequire two devices to obtain those two parameters [23, 24].

Estimation of blood pressure from the ECG as a main source was introduced by [25] depending on 6 features including (Age, Entropy, Fractal Dimension, Signal

Complexity and Signal Mobility) and using Naive Regression resulting in a mean error of 7.72 mmHg and a standard deviation error of 10.22 mmHg.

The aim of the present research is to study an indirect method for continuous categorization of the blood pressure through analysis ofthe ECGrecord as a unique source of information.

2. MATERIALS AND METHODS

A total of 715 ECG and their blood pressure signals were collected from different databases namelythe Zephyr database [26]and the Charis Physionet database [27]. The Number of signals recorded for each category and its code is shown in Table 1. Figure 1 illustrates the steps of the proposed method:

As shown in Fig. 1, the proposed method can be described as follows:

1- The signal is acquired from theonline databaseand saved in a .mat file. This file is saved as a matrix containing the ECG and blood pressure data.
2- Those values are passed through preprocessing modules to segment the signals to 30-second records, grouping the segments into the appropriate category (according to the rules of categorization stated by the American Heart Association [2] (see Table 1).
3- Then a Butterworth FIR band pass filter is applied to keep only the valid ECG information with a frequency band between 0.05 and 150 Hz.
4- The measured signals may introduce a signal shift that is not intrinsic to the data. These trends sometimes prevent data analysis, so trend removal is applied to all signals.
5- Amplitude normalization and resampling at 50 samples/second is next applied to all signals.
6- R-wave detection using Fourier transformation is applied. From the detected R-wave the heart rate variability can be estimated [27, 28].
7- The R-wave detection process is used to calculate the R-R interval.
8- 27 different statistical, texture, time domain, and age features are extracted (see Section 3.1).

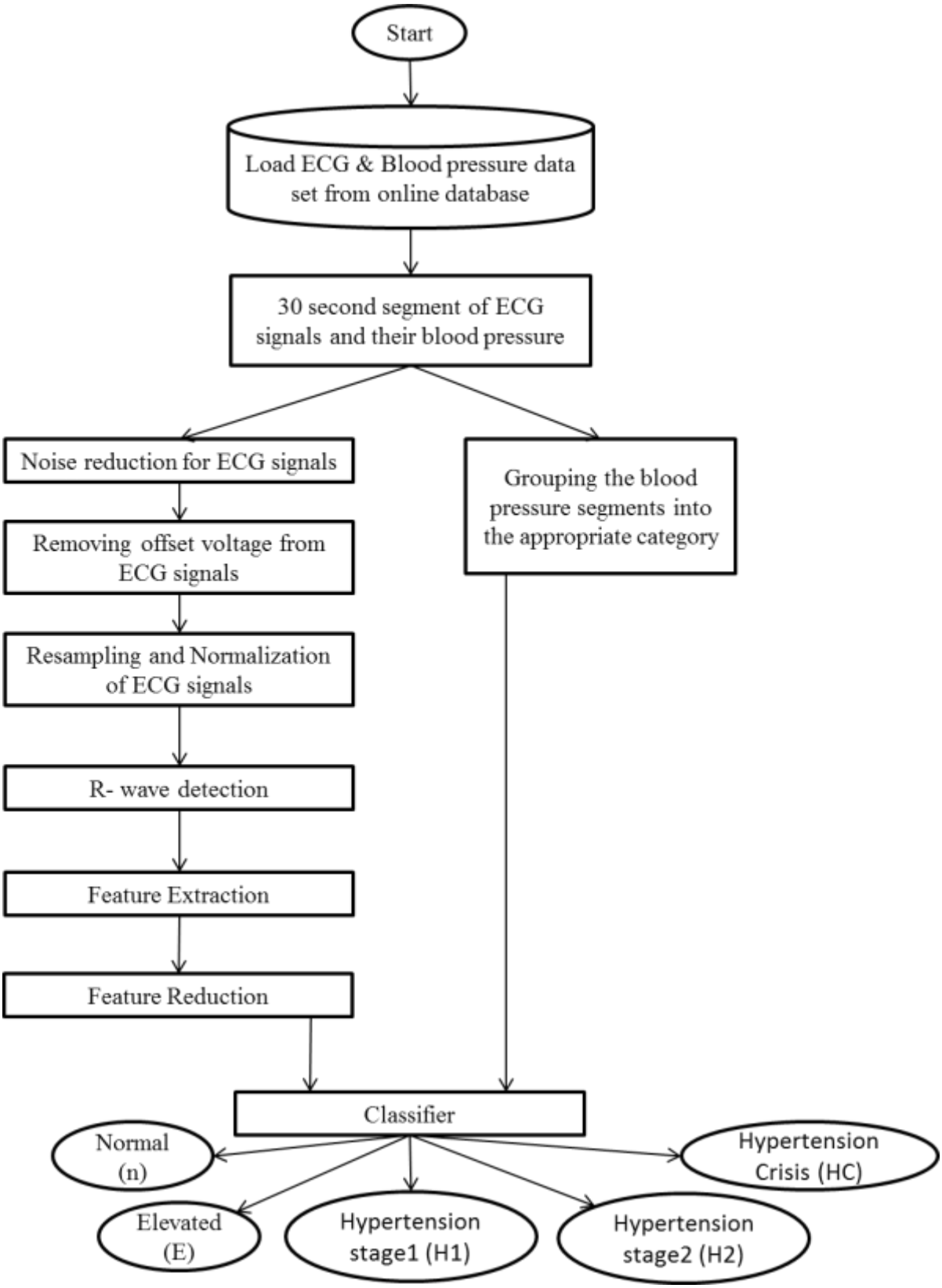

Fig. 1. Flowchart for proposed methodology.

9- Extracted features may contain features that are either correlated or irrelevant, and so they may differently affect the overall accuracy of the system. Thus, feature selection is important because it produces the minimum feature set with the highest classification power. Feature selection is applied using WEKA tools. WEKA is a data analysis software tool that implements a series of machine learning algorithms for data mining activities(i.e., feature selection and classification) [30]. The Wrapper method with a greedy stepwise and backward direction search algorithm is applied for feature selection. As a matter of fact, feature selection reduced thefeature set to ten features (Mean, Standard deviation, Kurtosis, Contrast 3, Contrast 4, Mobility, Homogeneity 3, Average heart rate, Standard deviation of the R-R series, and Average Heart Rate Variability).
10- Naïve Bayes, artificial neural network, and support vector machine classifiers are proposed for this studyand implemented using WEKA (see section 2.2).
11- At the end of the algorithm we applySystemTesting and Evaluation (see section 2.3 and 2.4).

2.1 Feature Extraction

Based on traditional features extracted from the processed ECG signal, in addition to features introduced by others who addressed the topic of categorizing blood pressure by using ECG analysis; 27features including statistical, texture, time domain, and age features were extracted as follows:

2.1.1 Statistical Features

Statistical feature and it contain 4features**;** Mean, Standard deviation, Skewness, and Kurtosis.

2.1.1.1Mean

For each ECG signal, X with a number of samples$N$, the mean is defined by Eq. (1):

$$Mean = \mu = \frac{1}{N}\sum_{i=1}^{N} X(i) \quad (1)$$

2.1.1.2 Standard deviation

The standard deviation describes the dispersion of the different samples, *X (i)*, within an ECG signal (X). It is calculated by Eq. (2):

$$standard\ deviation = \sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}[X(i)-\mu]^2} \quad (2)$$

Where *N* = total number of samples

2.1.1.3 Skewness

It measures the asymmetry of the sample distribution in the signal and is calculated by:

$$Skewness = S = \frac{1}{N}\sum_{i=1}^{N}[\frac{X(i)-\mu}{\sigma}]^3 \quad (3)$$

Where σ= standard deviation.

2.1.1.4 Kurtosis

It measures the peakness of the probability distribution of the sample as calculated by:

$$Kurtosis = K = \frac{1}{N}\sum_{i=1}^{N}[\frac{X(i)-\mu}{\sigma}]^4 \quad (4)$$

2.1.2 Texture analysis

The texture feature set contains 17 features which are described as follows:

2.1.2.1 Entropy

It is a measure of the randomness of the signal and is calculated according to Eq. (5). The decrease in entropy often indicates disease [31].

$$Entropy = \sum_{i=1}^{L} P_i \log \frac{1}{P_i} \quad (5)$$

P_i is the probability of occurrence signal amplitude level'i' within the ECG signal record, and L is the total number of levels.

2.1.2.2 Contrast

It measures the intensity contrast between every sample in the signal and its neighbors [32]. In our paper we used the relation between the samples and up to theirfourth neighbor (the number of neighbors was chosen empirically) to calculate Contrast1, Contrast2, Contrast3, and Contrast 4, as given by:

$$Contrast1 = C1 = \sum_{i=2}^{N-1} (i-1)^2 * X_i \quad (6)$$

$$Contrast2 = C2 = \sum_{i=3}^{N-1} (i-2)^2 * X_i \quad (7)$$

$$Contrast3 = C3 = \sum_{i=4}^{N-1} (i-3)^2 * X_i \quad (8)$$

$$Contrast4 = C4 = \sum_{i=5}^{N-1} (i-4)^2 * X_i \quad (9)$$

2.1.2.3 Correlation

It measures how correlated a sampleis with its neighbors in the signal [31].In our paper we used the relation between the samples and up to the fourth of its neighbors to calculate Correlation 1, Correlation 2, Correlation 3, and Correlation 4, as given by:

$$Correlation1 = Corr1 = \sum_{i=1}^{N-1} \frac{(i-\mu)(i+1-\mu) * X_i}{\sigma^2} \quad (10)$$

$$Correlation2 = Corr2 = \sum_{i=1}^{N-2} \frac{(i-\mu)(i+2-\mu) * X}{\sigma^2} \quad (11)$$

$$Correlation3 = Corr3 = \sum_{i=1}^{N-3} \frac{(i-\mu)(i+3-\mu) * X_i}{\sigma^2} \quad (12)$$

$$Correlation4 = Corr4 = \sum_{i=1}^{N-4} \frac{(i-\mu)(i+4-\mu) * X_i}{\sigma^2} \quad (13)$$

2.1.2.4 Energy

It is measure the sum of the squared samples for the signal, as given by:

$$Energy = E = \sum_{i=1}^{N} |X_i|^2 \quad (14)$$

2.1.2.5 Homogeneity

It is a measure of the sample distribution in the ECG signal relative to its neighbors [31]. In our paper we used the relation between the samples and up to the fourth of their neighbors to calculate Homogeneity1, Homogeneity2, Homogeneity3, and Homogeneity4 as given by:

$$\text{Homogeneity1} = H1 = \sum_{i=2}^{N-1} \frac{X_i}{1+|i-1|} \quad (15)$$

$$\text{Homogeneity2} = H1 = \sum_{i=3}^{N-1} \frac{X_i}{1+|i-2|} \quad (16)$$

$$\text{Homogeneity3} = H1 = \sum_{i=4}^{N-1} \frac{X_i}{1+|i-3|} \quad (17)$$

$$\text{Homogeneity4} = H1 = \sum_{i=5}^{N-1} \frac{X_i}{1+|i-4|} \quad (18)$$

2.1.2.6 Mobility

Signal mobility is the first order variation of the signal [31] and is given by:

$$Mobility = \frac{\sqrt{\frac{\sum_{j=2}^{N-1}(X_{j-1}-X_j)^2}{N-1}}}{\sqrt{\frac{\sum_{i=1}^{N}X_i{}^2}{N}}} \quad (19)$$

2.1.2.7 Signal Complexity

Signal Complexity is the second order variation of the signal [31],as given:

$$complexity = \sqrt{\frac{\frac{\sum_{k=3}^{N-2}(X_{k-2}-2*X_{k-1}+X_k)^2}{N-2}}{\frac{\sum_{j=2}^{N-1}(X_{j-1}-X_j)^2}{N-1}} - \frac{\frac{\sum_{j=2}^{N-1}(X_{j-1}-X_j)^2}{N-1}}{\frac{\sum_{i=1}^{N}X_i{}^2}{N}}} \quad (20)$$

2.1.2.8 Fractal Dimensions

The fractal dimension is a measure of self-similarity and describes the basic pattern hidden in the signal. It acts as an enlarger, magnifying different parts of the signal and comparing it with the whole signal. The Higuchi algorithm is one of the most efficient ways to calculate fractal dimensions, and we used it in our implementation [33].

2.1.3 Time domain analysis

Using the Fourier transform, the R wave can be identified, and the distance between every two successive R waves can be computed. The following 5 features were extracted as a follows:

1- Average Heart Rate (HR).
2- Standard Deviation of the Heart Rate.
3- Standard Deviation of the R-R interval, where the R-R interval is the time interval between two successive R-peaks in the ECG signal.
4- Percentage of QRS intervals that identify R-peaks in an ECG signal, which in that consequence are specifically longer than 50 msec (corresponding to the normal QRS interval in a normal ECG).
5- Average Heart Rate Variability [27, 28].

2.1.4 Age feature

The correlation between age and blood flow has been demonstrated by a mathematical model [34]. That explains the effect of vessel size on blood flow. In fact, age has a direct influence on the atrial wall properties; the blood vessels become tougher. As a result, the systolic pressure increases [34]. Table 2 shows the different age groups.

Table 2. Age Group Feature.

Group number	Age (years)
1	<20
2	21-35
3	36-50
4	>50

2.2 Classifier

In this paper, we selected three nonlinear standard machine learning algorithms to classify Blood pressure (Naïve Bayes (NB) classifier, support vector machine (SVM) and artificial neural network (ANN)) to discuss the power of machine learning regarding the identificationof the blood pressure class based on the features extracted from ECG.

2.3 Testing

To test the strength and reliability of the developed classifier, we use a cross-validation approach.

2.3.1 Cross validation

Because of the number of recorded signals in each category in the database is not equal Table 1, we used cross-validation. Cross-validation is a statistical method to identify the best classifier among a group of pre-chosen and constructed classifiers.

The idea is to group the available datasets into equally sized *k*groups, basically 10 groups. Initially, nine of the ten groups serve as the training set, whereas the remaining group is selected as the test group. The resultingevaluation score (either

performance measure or error rate) is calculated. This step is known as “train and evaluate” and is then repeated for the othernine instances.

By the end of the 10 rounds, we obtain 10 evaluation scores (one for each round, using a specific classifier), The average of the ten evaluation scores is finally used to cross-validate this particular classifier [35].

This average is evaluated for all pre-chosen classifiers (SVM, ANN, and NB).

2.4 Evaluation

We evaluate the model using the following parameters[36]:

2.4.1 Accuracy.

This is the percentage of correctly classified instances in each classification modeland it is defined by:

$$\text{Accuracy} = (TP + TN) \,/\, (TP + TN + FN + FP) \tag{21}$$

Where

True positive (TP) = number of positive samples correctly predicted.

False negative (FN) = number of positive samples wrongly predicted.

False positive (FP) = number of negative samples wrongly predicted as positive.

True negative (TN) = number of negative samples correctly predicted.

2.4.2 Sensitivity

The sensitivity or the true positive rate (TPR) measures the percentage of relevant data that was returned by the classifier. A high value means that the model returns most of the relevant data. Sensitivity is defined by:

$$\text{Sensitivity} = \text{TP} \,/\, (\text{TP} + \text{FN}) \tag{22}$$

2.4.3 Precision

Precision measures the exactness of the relevant data retrieved. High precision means that the model returns more relevant data than irrelevant data. Precision or positive predictive value (PPV) is defined by:

$$\text{Precision} = TP \,/\, (TP + FP) \tag{23}$$

2.4.4 F-measure

F-measure is defined by:

$$\mathrm{F-measure} = 2 * \left(\frac{Sensitivity * Precision}{(Sensitivity + Precision)}\right) \quad (24)$$

Where:

$$Precision = \frac{TP}{TP + FP} \quad (25)$$

2.4.5 ROC

ROC is a representation of the relationship between sensitivity and specificity, which is useful for determining the best model.

2.4.6 Root mean squared error

This as a measure of the differences between sample/population values predicted by a model or an estimator and the values actually observed. It represents the sample standard deviation of the differences between predicted and observed values.

2.4.7 Kappa statistic

It is a measure the relationship between classified instances and true classes. It usually lies between [0, 1]. If the value is 1 means perfect relationship while 0 means random guessing, and it is defined by:

$$\mathrm{Kappa} = \frac{\mathrm{accuracy} - \mathrm{expected\ accuracy}}{1 - \mathrm{expected\ accuracy}} \quad (26)$$

Where:

$$\mathrm{Expected\ accuracy} = \frac{((\mathrm{TP} + \mathrm{FN}) * (\mathrm{TP} + \mathrm{FP}) + (\mathrm{TN} + \mathrm{FP}) * (\mathrm{TN} + \mathrm{FN}))}{(\mathrm{TP} + \mathrm{TN} + \mathrm{FN} + \mathrm{FP})^2} \quad (27)$$

3. RESULTS AND DISCUSSION

We applied the proposed algorithm to 715 ECG traces and their corresponding blood pressure signals. Four statistical features (Mean, Standard deviation, Skewness, and Kurtosis) were extracted. Additionally, seventeen texture features (Contrast,

Correlation, and Homogeneity) with up to the fourth neighbors, as well as the Entropy, Energy, Mobility, Signal Complexity and Fractal Dimensions) were also extracted.

Moreover, we also made use offive time domain features depending on R- wave detection (Average heart rate, Standard deviation of heart rate, Standard deviation of the R-R series, the percentage of this number and the Average heart rate variability). Finally, we took the age into consideration as one of the crucial features.

Features selection using the greedy stepwise with backward direction search Wrapper algorithm reduced the feature set to ten features (Mean, Standard deviation, Kurtosis, Contrast3, Contrast4, Mobility, Homogeneity3, Average heart rate, Standard deviation of the R-R series, and Average Heart Rate Variability). A 10-feature vector is obtained for eachsignal to finally produce a715x10matrixas an input array for the classifier. Our studies were performed using the WEKA software (V 3.8.1).

Table 3 shows the precision, sensitivity, F-measure and ROC area measure for each class, in addition to Accuracy, Kappa statistic, and Mean absolute error foreach of the SVM, ANN and NB classifiers. Table 3 shows that accuracy of all classifiers is higher than 96%.

For the SVM classifier with a complexity parameter equals to 500 which is selected empirically the accuracy reached 98.18% with a Kappa statistic of 0.97. The minimum sensitivity was 0.867 for the N class, and the maximum sensitivity was unity for class H1. The minimum precision of 0.886 was for the N class, and 0.995 was the highest sensitivity for either class H1 and H2.

For the ANN classifier with one hidden layer and fifteen nodes - the number of nodes was chosen empirically -the accuracy was 96.5% with a Kappa statistic of 0.943. The minimum precision was 0.756 for the N class while the maximum one was 0.997 for class H2. The sensitivity for class N had a minimum value of 0.756, while the maximum sensitivity was unity for the H1 class.

For the NB classifier the accuracy reached 96.08 % with a Kappa statistic of 0.937. The minimum precision was 0.667 for the N class, and the maximum one of 0.995 was for the H2 class. The sensitivity varied from 0.75 for the E class to 1 for the H1 class. The confusion matrix for the three classifiers is shown in Table 4.

Table 3. Classifier performance evaluation for the selected 10-tuple feature vector.

classifier	Blood Pressure Class code	Precision	Sensitivity	F-Measure	ROC Area	Kappa statistic	Mean absolute error	Accuracy %
SVM	N	0.886	0.867	0.876	0.948	0.97	0.317	98.18
	E	0.949	0.938	0.943	0.994			
	H1	0.995	1	0.997	0.999			
	H2	0.995	0.997	0.996	0.995			
	HC	0.917	0.917	0.917	0.923			
ANN	N	0.756	0.756	0.756	0.92	0.943	0.111	96.5
	E	0.883	0.85	0.866	0.988			
	H1	0.984	1	0.992	0.999			
	H2	0.997	0.997	0.997	0.998			
	HC	0.917	0.917	0.917	0.921			
NB	N	0.667	0.889	0.762	0.955	0.937	0.118	96.08
	E	0.938	0.75	0.833	0.986			
	H1	0.99	1	0.995	0.999			
	H2	0.995	0.995	0.995	0.996			
	HC	1	0.917	0.957	0.941			

Table 4. Confusion matrix.

classifier	Real/Predicted	N	E	H1	H2	HC
SVM	N	39	3	0	2	1
	E	5	75	0	0	0
	H1	0	0	190	0	0
	H2	0	0	1	387	0
	HC	0	1	0	0	11
ANN	N	34	8	1	1	1
	E	11	68	1	0	0
	H1	0	0	190	0	0
	H2	0	0	1	387	0
	HC	0	1	0	0	11
NB	N	40	3	1	1	0
	E	19	60	0	1	0
	H1	0	0	190	0	0
	H2	0	1	1	386	0
	HC	1	0	0	0	11

The scarcity of the data set signals that belong to either the N or the HC class affects both the sensitivity and precision for these two groups, which in turn affects the

overall performance. The representative signal percentage of the N and HC classes are 6.2% and 1.6%, respectively of the entire database, while the percentage of Hypertension Stage 2 (H2) and Hypertension Stage 1 (H1) are 26.5% and 54.2% respectively of the same database by referring to Table 1.

4. CONCLUSION

Testing and evaluating the proposed methodology for continuous categorization of the blood pressure through the analysis of the ECG record as a single source of information have been done by means of three different classifiers. Results reveal accuracies of 98.18%, 96.5% and 96.08% for the SVM, ANN and NB classifiers, respectively. We can conclude that using the SVM classifier we can reach an acceptable accuracy of 98.18% forthe continuous categorization of the blood pressure through analysis of the ECG record as a single source of information with the help of only 10 features.

Our intended future work is to create a database consisting of balanced classes to account for the scarcity of the data set signals that belong to either the Normal or the hypertensive classes. We also aim to improve the methodology to be able to estimate the actual values of the systolic blood pressure (SBP) and the diastolic blood pressure (DBP) using regression techniques.

DECLARATION OF CONFLICT OF INTERESTS

The authors have declared no conflict of interest.

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تصنيف ضغط الدم من خلال اشارة رسم القلب

تعتبر القراءة المستمرة للعلامات الحيوية في وحدة العناية المركزة من الأدوار الرئيسية للطبيب ، مما يسمح له بالتدخل في الوقت المناسب. قياس ضغط الدم المستمر مهمة صعبة طالما أنها تعتمد على طرق المعتادة من جهاز ضغط الدم الزئبقي والطرق الأخرى.هدف هذا البحث هو تصنيف ضغط الدم عن طريق معالجة وتحليل اشارة رسم القلب الكهربائي منفردة باستخدام طرق معالجة الاشارات. تبدأ المعالجةبتطبيق المرشح بتروورث علي إشارة رسم القلب. يتبعها إزالة الاتجاه وتطبيع للإشارة 27 ميزة يتم استخراجها.يتم تطبيق طرق اختيار المميزات لاختيار اكثرهم فاعلية ودقة، وتم تقليل النتيجة إلى ١٠ مميزات. النتائج النهائية تبلغ ٩٨.١٨٪ باستخدام مصنف متجهات آلات دعم التمييز. كما تم استخدام المصنفات الأخرى مثل الشبكات العصبية الاصطناعية والتصنيف Naïve Bayes (NB) ولكن أعطى دقة أقل ٩٦.٥ ٪ و ٩٦.٠٨ ٪ ، على التوالي.