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An Efficient Paroxysmal Atrial Fibrillation Prediction Method Using CWT and SVM

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ABSTRACT—Paroxysmal Atrial Fibrillation (PAF) is the most commonly occurring arrhythmia and its prevalence increases with age. This paper presents an efficient method for detection and prediction of (PAF) using PAF prediction challenge database (afpdb) to locate normal person from person who suffers from PAF. We extract 11 features from 100 ECG recorded signals database with the aid of continuous wavelet transform (CWT), to allow accurate extraction of feature from non-stationary signal like ECG, and a Support Vector Machines (SVM) to classify the patterns inherent in the features extracted. We divide the 30-min preceding the PAF into 6 periods with 5-min each. In each suggested period we get the classification result using (SVM). The measured sensitivity, specificity, positive predictivity and accuracy show better and significant results comparable to the other results obtained in the same field in the literature.

Index Terms—PAF prediction, ECG signal, continuous wavelet transform, support vector machine, statistical parameters.

1. INRODUCTION

Paroxysmal atrial fibrillation (PAF) of the heart muscle is defined as short duration episodes of AF lasting from 2min. to less than 7 days, while chronic AF is defined as lasting more than 7 days. The main reason for this is not the immediate effect of the onset of atrial fibrillation over the patient's health (AF detection) but the long-term effects: increase in heart muscle fatigue, increase in thromboembolic and stroke events due to the formation of blood clots and an irregular onset that makes it hard to detect on normal ECG tests. Thus it is necessary for cardiologists to benefit from a robust and precise tool that could predict the onset of such events, in order to prevent them by defibrillation, drug treatment and anti-tachycardia pacing techniques. The automated method to predict the onset PAF is interesting topic to help treating this problem.

During recent years several researchers proposed many techniques to predict the onset of PAF. Useful reviews describing different techniques for PAF or chronic AF prediction, from technical to clinical points of view [1-5]. The "Computers in Cardiology Challenge 2001" revealed a maximum obtained accuracy of about 80% [6-8]. Thong [9] reports a sensitivity and specificity of 89% and 91% respectively, by analysis of atrial premature complexes (that trigger 93% of PAF episodes).

Support vector machine (SVM) in recent years has proved to be an advanced tool in solving classification [11-13], wavelets proved usefulness in feature extraction from non-stationary signal like ECG [14-17]. In general, these above prediction models are able to detect the transition to PAF events with accuracies of 70–90%, by means of records of at least tens of minutes and rather complex analysis procedures.

In the present work, several features are extracted with the aid of CWT which convert the time domain signal to time-frequency domain where several features can be carefully extracted, the extracted features are then applied to SVM to classify the normal object from that one who suffers from PAF.

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2. MATERIAL AND METHODS

The database used for this task was PAF Prediction Challenge Database 2001 from physionet.org. It consists of 3 record sets: the first one has records that begin with the letter 'n' and comes from 50 subjects who do not have documented PAF. The length of these records is 30 min. The second record that begin with letter 'p' comes from 25 subjects who have documented PAF, and it is divided into two types, the even one has a record of 30 min preceding the PAF, and the odd one has a record of 30 min. but distant from PAF. All the previous record has a continuation 5 min record with a letter 'c'. The third record contains 100 annotated recordings for testing with a letter't' of 30 min. and unknown documentation. Each record contains two channels simultaneous recorded Holter ECG signal digitized at 128 Hz with 12 bit resolution over a 20 mV range.

We used in this task both channels of the ECG signal (100 records) to create the database summarized in Table 1.

The block diagram of the proposed method is shown in Fig. 1; each block is described in more details.

Table 1 The database used for PAF prediction

Learning set		Testing set
Non-PAF recording(n)	PAF-recording(p-even)	PAF and Non-PAF
30(random selected)	30(randomly selected)	40 (randomly selected)
60		40

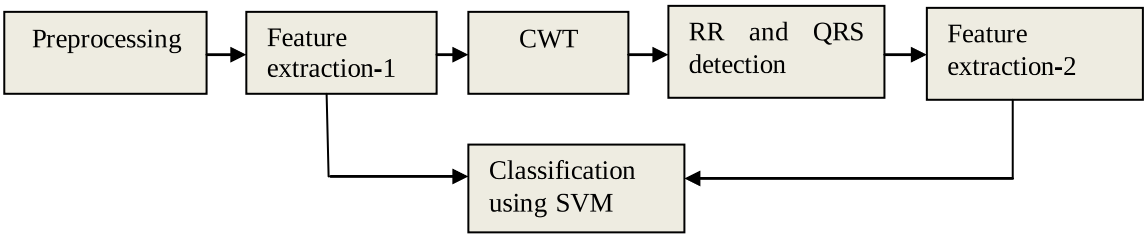

Fig. 1 Block diagram of the proposed method

2.1Preprocessing.

The ECG signal within the database can be affected by many interfering signals such as the 50 Hz power line interference and the baseline wandering. These interfering noises are eliminated first by means of a 5-15 Hz bandpass filter. For lowering interference noise, a median filter was used.

2.2Continuous Wavelet Transform (CWT)

CWT allows a time domain signal to be transformed into time-frequency domain where frequency characteristics and the location of particular features in a time series may be highlighted simultaneously. Thus it allows accurate extraction of feature from non-stationary signal like ECG [14]. The CWT wavelet transform is a tool that divides up data, functions, or operators into different frequency components and then studies each component with a resolution matched to its scale. Unlike the short time Fourier transformation (STFT) the wavelet transformation has very good time and frequency resolution making it ideal in the analysis of non-stationary signals such as an ECG signal.

The continuous wavelet transformation (CWT) of a signal x(t) is the convolution product of x (t) with a scaled and translated kernel function [15]

$$CWT_x^{\phi} = \frac{1}{\sqrt{|s|}}\int_{-\infty}^{\infty} x(t)\phi\left(\frac{t-\tau}{s}\right)dt \qquad (1)$$

Where $\Phi((t-\tau)/s)$is a scaled and translated (shifted) version of a mother wavelet which is the basic unit of wavelet decomposition, s is a scale parameter and τ is a space parameter.

To analyze the CWT coefficients obtained for ECG signal of PAF record and non-PAF, predominant frequency vs. time plot of selected ECG signal has been obtained. From these plots translation, scale and coefficient values of the peaks, which represent P, Q, R, S,T and U wave has been extracted for PAF and non-PAF records. Fig. 2 and Fig. 4 show the normal ECG signal plot and the ECG signal preceding PAF plot respectively. Fig. 3 and Fig. 5 illustrates the difference in the amplitude and duration of RR and QRS among PAF and non-PAF records at different scales with the aid of CWT.

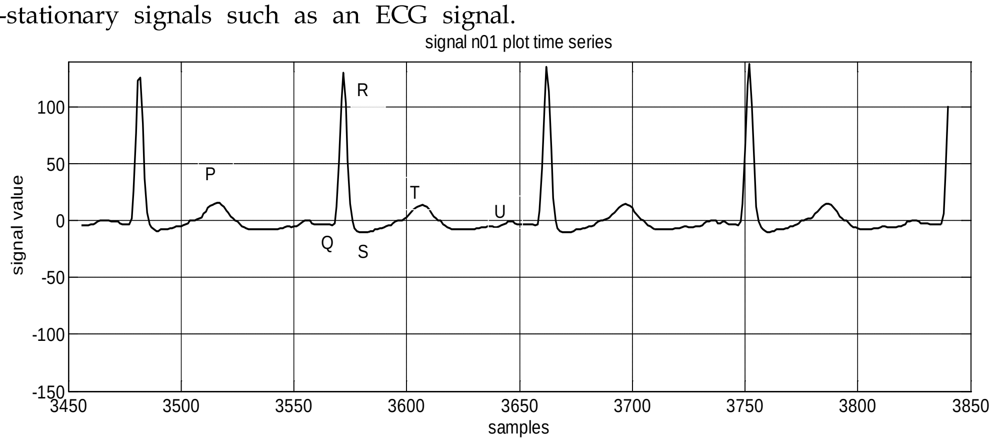

Fig. 2 Normal ECG signal from n01 record

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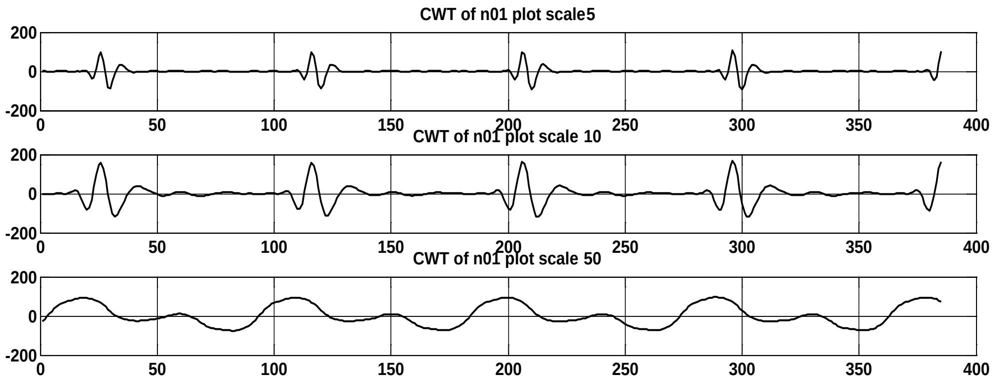

Fig. 3 CWT of the normal record at scales 5, 10, 50

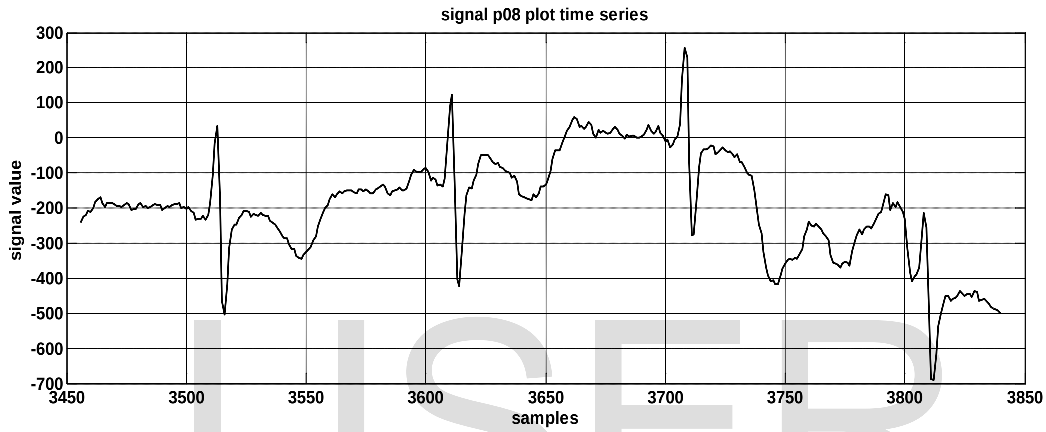

Fig. 4 ECG signal preceding PAF (record p08)

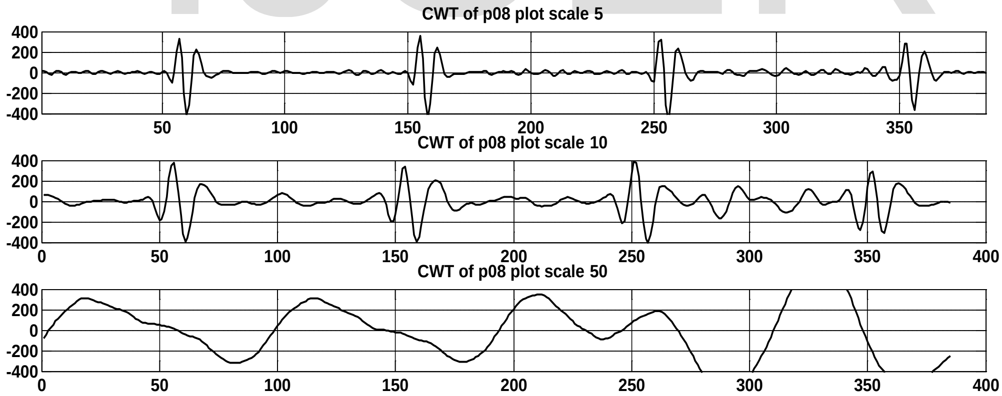

Fig. 5 CWT of the PAF record at scales 5, 10, 50

2.3Feature Extraction.

We utilized 11 features: 3 (1- 3) related to signal statistical and 8 (4-11) by mean of continuous wavelet transform as follows:

(1) Sigmean: mean value of the signal during all period (30 min), the histogram of the obtained results is illustrated in Fig. 6. We can note that most of PAF records have a high negative value.

(2) Sigstd: the standard deviation of the recorded signal, the histogram of the obtained results is illustrated in Fig. 7. We can note that most of PAF records have a high positive value.

(3) Sigdiff: difference between the maximum signal and the minimum signal, the histogram of the obtained results is illustrated in Fig. 8. We can note that most of PAF records have a small positive value.

(4) RRno: number of RR interval inside each period. We first detect R peak inside each period, and with the aid of CWT, we can discriminate the extremes values and their locations.

(5) RRdiff: The difference between max. RR interval and min. RR interval inside each period.

(6) RRmax : maximum values of RR interval inside each period

(9) RRmean: mean values of RR interval inside each period

(7) RRrms : root mean square values of RR interval inside each period

(8) Ramp : mean value of R peak inside each period

(10) RRstd : standard deviation of RR interval inside each period

(11) QRSmean: mean value of QRS duration inside each period

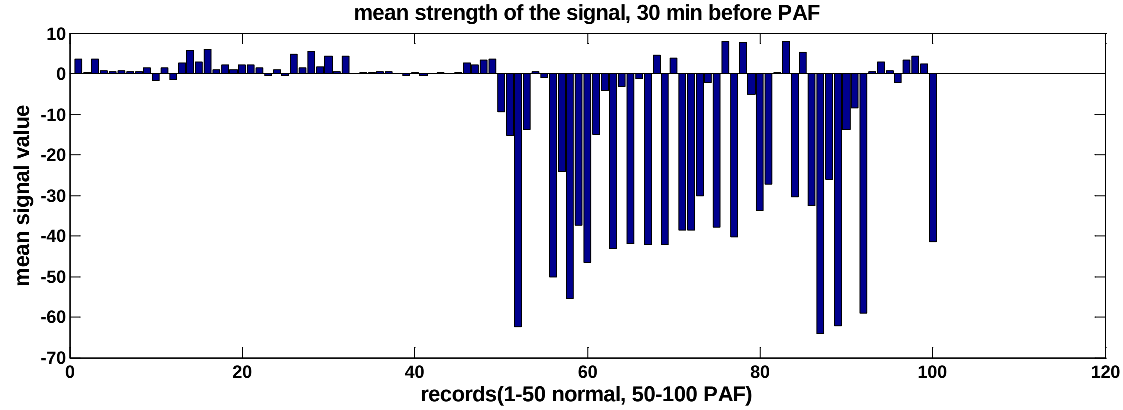

Fig. 6 Histogram of the mean signal for all records.

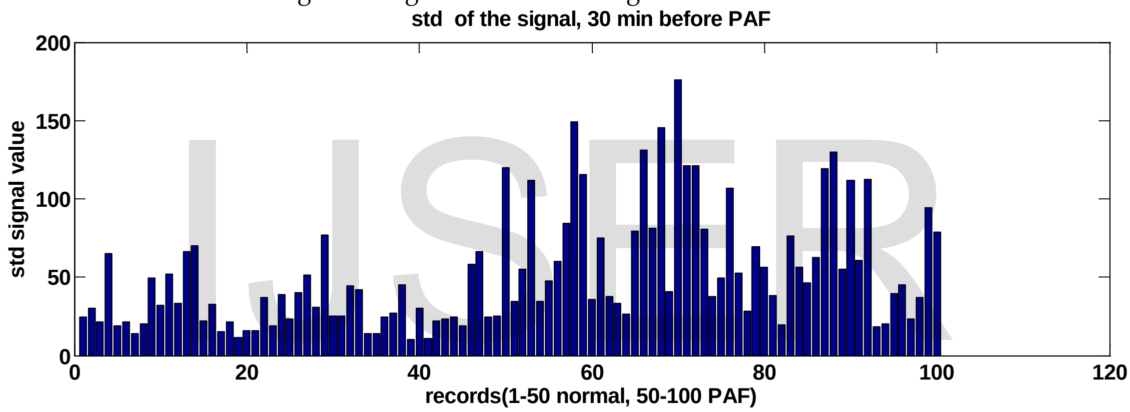

Fig. 7 Histogram of the standard deviation of the signal for all records.

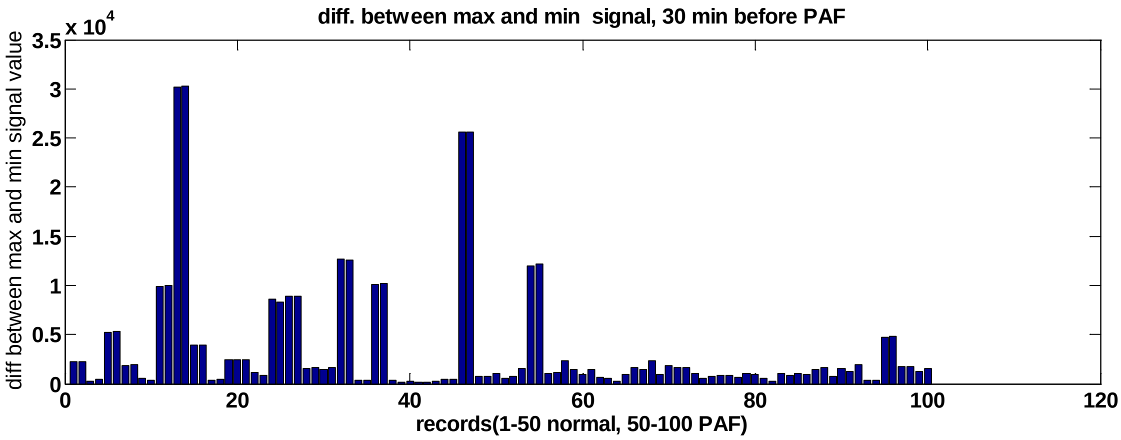

Fig. 8 Histogram of the signal difference between (max. and min.) signal for all records.

2.4 Support Vector Machine (SVM).

The SVM is a discriminative classifier formally defined by margins) between the two classes of the training samples a separating hyperplane (the plane with maximum within the feature space by focusing on the training cases placed at the edge of the class descriptors so not only an optimal hyperplane is fitted, but also training samples are effectively used. In that way high classification accuracy is achieved with small training sets [12].

In soft margin classification, the SVM algorithm can be summarized as the following optimization problem: given a training set (xi, yi), i=1,2,..,n

$\min[\frac{1}{2}W^TW + C\sum_{i=1}^{n}\xi_i]$ for all {(xi ,yi)}

Subjected to: yi (wT Φ(xi)+ b) ≥ 1- ξ and ξi ≥ 0 for all i (2)

Where : Φ(x) is a nonlinear function that maps x into a higher dimensional space.

W, b, and ξ are the weight vector, bias, and slack variable respectively. C is a constant determined a priori. Parameter C can be viewed as a way to control over fitting. Most "important" training points are support vectors; they define the hyperplane. Quadratic optimization algorithms can identify which training points xi are support vectors with non-zero Lagrangian multipliers αi. By constructing a Lagrangian and transforming it into a dual maximization of the function Q(α), defined as follows:

max Q(α) =Σαi - ½ΣΣ αi αj yi yj K(xi, xj)

Subject to: $\sum_{i=1}^{n}\alpha_i y_i = 0;\quad 0 \le \alpha_i \le C,\quad$ for i= 1, 2, …,n (3)

Where K(xi, xj) = $\varphi(x_i)^T\varphi(x_j)$ is the kernel function and αi is vector of non negative Lagrange multipliers. The kernel function plays the role of the dot product in the feature space.

Suppose that the optimum values of the Lagrange multipliers are denoted α0, it is then to determine the corresponding optimum value of the linear weight vector wo and the optimal hyperplane as in (4) and (5), respectively:

$$w_o = \sum_{i=1}^{n}\alpha_{o,i}\, y_i \phi(x_i) \quad (4)$$

$$\sum_{i=1}^{n}\alpha_{o,i}\, y_i K(x_i, x_j) + b \quad (5)$$

The solution is

f(x)=sign $(\sum_{i=1}^{n}\alpha_{o,i}\, y_i K(x_i, x_j) + b)$ (6)

- Kernel functions may be one of the following types:
- Linear: K(xi,xj)= xi Txj (7)
- Polynomial of power p: K(xi,xj)= (1+ xi Txj)p (8)

Gaussian (radial-basis function network):

$$K(\mathbf{x_i}, \mathbf{x_j}) = \exp(-\frac{\|\mathbf{x_i} - \mathbf{x_j}\|^2}{2\sigma^2}) \quad (9)$$

- Sigmoid: K(xi,xj)= tanh(β0xi Txj + β1) (10)

In this task, we used radial basis function (RBF) as kernel function where:

σ (kernel width) : is the distance between closest points with different classifications

C, σ were experimentally defined to achieve the best classification result.

3 RESULTS AND DISCUSSION

To evaluate the performance of the proposed method during 30-min preceding the (PAF), we divide 30-min period into 6 intervals, 5-min each. Four measures are used as follows:

$$\text{Sensitivity}(\%) = \frac{TP}{TP+FN}\,100 \quad (11)$$

$$\text{Specificity}(\%) = \frac{TN}{TN+FP}\,100 \quad (12)$$

$$\text{PositivePredicitivity}(\%) = \frac{TP}{TP+FP}\,100 \quad (13)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}\,100 \quad (14)$$

Where:

TP: True Positive, when an object having (PAF) is classified correctly.

TN: True Negative when a normal object is classified correctly.

FN: False Negative when an object having (PAF) is classified as normal incorrectly

FP: False Positive when a normal person is classified as having PAF incorrectly

To optimize the learning cost and the classification performance, the SVM classifier parameters, kernel width σ and regularization constant C, must be chosen effectively [12]. So we chose the parameters σ and C as 10 and 1 respectively.

To evaluate the performance of the proposed classifier (SVM), we used 60 records (30 n and 30 p) for training and 40 records (20 n and 20 p) for testing. The four previously mentioned measures are calculated in each 5-min interval. The experiments were repeated 5 trials. In each trial a different set of randomly shuffled samples is done and the significant results were tabulated in Table 2

The result of SVM classifier in training data set and testing another data set (when two features) is illustrated in Fig. 9

We can deduce the following points from analysis of the obtained results:

- We can predict PAF efficiently even in 30 min prior to PAF
- The average percentage of the sensitivity, specificity, positive predictivity and accuracy are higher during 5-min interval preceding the PAF directly.
- The efficiency of the CWT to allow accurate extraction of features from non-stationary signal like ECG.

Trial 1				
Period (5min)	Sensitivity (%)	Specificity (%)	Positive predicit.	Accuracy (%)

			(%)	
30 min prior to PAF	90	90	90	90
25min prior to PAF	90	100	100	95
20min prior to PAF	85	100	100	92.5
15 min prior to PAF	85	100	100	92.5
10 min prior to PAF	90	100	100	95
5 min prior to PAF	90	100	100	95
Trial 2				
30 min prior to PAF	90	100	100	95
25min prior to PAF	85	100	100	92.5
20min prior to PAF	80	100	100	90
15 min prior to PAF	80	100	100	90
10 min prior to PAF	85	100	100	92.5
5 min prior to PAF	95	95	95	95
Trial 3				
30 min prior to PAF	85	100	100	92.5
25min prior to PAF	85	100	100	92.5
20min prior to PAF	85	100	100	92.5
15 min prior to PAF	85	100	100	92.5
10 min prior to PAF	85	100	100	92.5
5 min prior to PAF	95	100	100	97.5
Trial 4				
30 min prior to PAF	90	100	100	95
25min prior to PAF	85	90	89.47	87.5
20min prior to PAF	80	100	100	90
15 min prior to PAF	80	100	100	90
10 min prior to PAF	85	100	100	92.5
5 min prior to PAF	95	85	86.36	90
Trial 5				
30 min prior to PAF	85	100	100	92.5
25min prior to PAF	80	90	88.88	85
20min prior to PAF	85	100	100	92.5
15 min prior to PAF	80	100	100	90
10 min prior to PAF	85	100	100	92.5
5 min prior to PAF	95	90	90.47	92.5
Average value				
30 min prior to PAF	88	98	98	93
25min prior to PAF	85	96	95.67	90.5
20min prior to PAF	83	100	100	91.5
15 min prior to PAF	82	100	100	91
10 min prior to PAF	86	100	100	93
5 min prior to PAF	94	94	94.36	94

Table 2: Performance evaluation in 5 Trials and the average through 6 intervals in each trial

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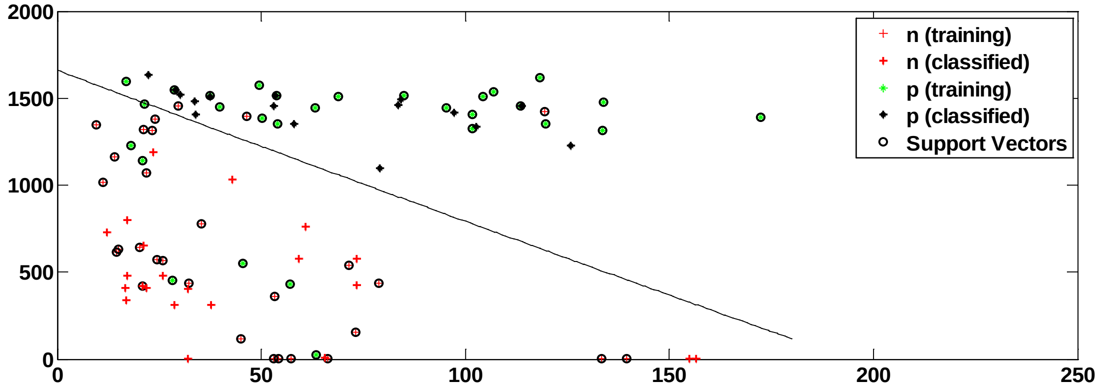

Fig. 9: SVM training and classification results

Table 3 Comparative results in the literature

Method	Literature	Sensitivity (%)	Specificity (%)
HRV	Hariton Costin, et al., 2013 [10]	84.51	83.93
MV		87.32	87.5
HRV+MV		89.44	89.29
K-nearest neighbor algorithm	M. Panusittikorn, et al., 2010 [16]	71.0	65.0
Proposed method	Ashraf, Hedi, 2013	94.0	94.0

- Robustness of (SVM) classifier to handle large feature spaces.
- Features like sigmean, sigstd, sigdiff, RRno, RRdiff Ramp and QRSmean enhance the SVM to distinguish between normal ECG record and PAF ECG record

The comparison between the obtained results and other results, in the same field, in the literature [10, 16]
is shown in Table 3

4 CONCLUSION

An efficient method in predicting PAF is introduced in this task. We extract 11 features from 100 ECG recorded signals of 'afpdp' database with the aid of CWT, to allow accurate extraction of feature from non-stationary signal like ECG, and a Support Vector Machines (SVM) to classify the patterns inherent in the features extracted. The obtained results show the efficiency of the proposed method in predicting the onset of PAF. The average personage of sensitivity, specificity, positive predictivity and accuracy are 94%, 94%, 94.36%, and 94% respectively, and these values overpass the obtained results in the literature

REFERENCES

[1] Poli S., Barbaro V., Bartolini P., Calcagnini G., Censi F., Prediction of Atrial Fibrillation from Surface ECG: Review of Methods and Algorithms. Ann I-st Super Sanità, 39, 2, 195−203, 2003.

[2] Bollmann A., Husser D., Mainardi L. et al., Analysis of Surface Electrocardiograms in Atrial Fibrillation: Techniques, Research, and Clinical Applications. Europace, 8, 911–926, 2006.

[3] Chiarugi F., New Developments in the Automatic Analysis of the Surface ECG: the Case of Atrial Fibrillation. Hellenic J. of Cardiology, 49, 207−221, 2008.

[4] Sörnmo L., Stridh M., Husser D., Bollmann A., Bertil Ollsen S., Analysis of Atrial Fibrillation: from Electrocardiogram Signal Processing to Clinical Management. Phil. Trans. of the Royal Society, A, 367, 235−253, 2009.

[5] S.Karpagachelvi, et al., ECG Feature Techniques- A Survey Approach. International Journal of Computer Science and Information Security, 8, 1, 76-80, 2010.

[6] Moody G.B., Goldberger A.L., McClennen S., Swiryn S.P., Predicting the Onset of Paroxysmal Atrial Fibrillation: the Computers in Cardiology Challenge 2001. Computers in Cardiology, 28, 113−116, 2001.

[7] De Chazal P., Heneghan C., Automated Assessment of Atrial Fibrillation. Computers in Cardiology, 28, 117−120, 2001.

[8] Maier C., Bauch M., Dickhaus H., Screening and Prediction of Paroxysmal Atrial Fibrillation by Analysis of Heart Rate Parameters. Computers in Cardiology, 28, 129−132, 2001.

[9] Thong T., McNames J., Aboy M., Goldstein B., Prediction of Paroxysmal Atrial Fibrillation by Analysis of Atrial Premature Complexes. IEEE Trans. on Biomed. Eng, 51, 4, 561−569, 2004.

[10] Hariton Costin, et al. A New Method for Paroxysmal Atrial Fibrillation Automatic Detection. Buletinul Institutului Politehnic din Iaşi Tome LIX (LXIII) Fasc. 1, 2013

[11] Graja S., Boucher J.M., SVM Classification of Patients Prone to Atrial Fibrillation. WISP 2005, IEEE Int. Symp. on Intelligent Signal Proc., University of Algarve, Faro, Portugal, 370−374, 2005.

[12] Maryam, Hassan, Detection of Atrial Fibrillation Episodes using SVM. 30th Annual International IEEE EMBS conference, Vancouver, British, Canada, 177-180, 2008.

[13] Argyro, et al., Robustness of Support Vector Machines-based Classification of Heart Rate Signals. Proceeding of the 28th IEEE EMBS Annual International Conference, New York City, USA, 2159-2162, 2006.

[14] Digvijay, et al., Wavelet Aided SVM Analysis of ECG Signals for Cardiac Abnormality Detection. IEEE Indicon conference, Chennai, India, 9-13, 2005.

[15] Erik Zellmer, et al., Highly Accurate ECG Beat Classification based on Continuous Wavelet Transformation and Multiple Support Vector Machine Classifiers. IEEE International Conference, 1-5, 2009

[16] M. Panusittikorn, et al., Prediction of Paroxysmal Atrial Fibrillation Occurrence with Wavelet-based Markers. IEEE International Conference, 342-345, 2010.

[17] A. K. M. Fazlul Haque, et al., Detection of Small Variations of ECG Features Using Wavelet. ARPN Journal of Engineering and Applied Sciences, 4, 6, 2009