
ECG signals classification: a review

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Abstract: Electrocardiogram (ECG), non-stationary signals, is extensively used to evaluate the rate and tuning of heartbeats. The main purpose of this paper is to provide an overview of utilizing machine learning and swarm optimization algorithms in ECG classification. Furthermore, feature extraction is the main stage in ECG classification to find a set of relevant features that can attain the best accuracy. Swarm optimization algorithm is combined with classifiers for the purpose of searching the best value of classification parameters that best fits its discriminant purpose. Finally, this paper introduces an ECG heartbeat classification approach based on the water wave optimization (WWO) and support vector machine (SVM). Published literature presented in this paper indicates the potential of ANN and SVM as a useful tool for ECG classification. Author strongly believes that this review will be quite useful to the researchers, scientific engineers working in this area to find out the relevant references.

Keywords: electrocardiogram; ECG; feature extraction; feature optimisation; classification; artificial neural networks; ANNs; support vector machines (SVMs).

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1 Introduction

The electrocardiogram (ECG) signal contains lots of pathological information about patient's heart processes. One important analysis in the ECG is the classification of heartbeats, which is important for the detection of arrhythmias (Kass and Clancy, 2005). Arrhythmias can be splits into life-threatening and non-life-threatening arrhythmias. Discovering has been made in Alonso-Atienza et al. (2014) to investigate the life-threatening arrhythmias. Heartbeat classification of long-term ECG recordings required for the diagnosis of non-life-threatening arrhythmias could be time-consuming and impractical, automatic algorithms exhibit a great aid. Therefore, the automatic heartbeat classification of the latter arrhythmias is worth studying. ECG which reveals the rhythm and activity of the heart is an important non-invasive clinical tool for cardiologists to diagnose various heart diseases. Many automatic ECG arrhythmia classification systems have been investigated using computational intelligence. A successful ECG arrhythmia classification sometimes contains three important procedures: feature extraction, feature selection, and classification. Feature extraction is an important procedure that usually influences the classification performance of any ECG arrhythmia classification system. Therefore, to extract relevant features and reduce their dimensions for classifiers to achieve the best classification results have become the primary stage for the ECG arrhythmia classification problems (de Chazal et al., 2004).

However, the classification of significantly different arrhythmias has limited applicability in practice, because there are several types of cardiac arrhythmias that are not noticeably different if to heart rate variability (HRV) information is used alone, but are quite common in patients (Jovic and Bogunovic, 2012; Kumar et al., 2015). The arrhythmias ought to be classified as accurately as possible in order to enable early detection of potentially significant cardiac disorders. Higher classification accuracies can be obtained by readjusting used kernel parameters of the classifier (Huang and Wang, 2006). Machine learning (ML) techniques such as artificial neural networks (ANN) and support vector machines (SVMs) (Vapnik, 1995) are used for diagnosis of cardiovascular diseases (CVDs).

Therefore, this paper focuses on the application of ANN and SVM to ECG classification, not easily discernible cardiac arrhythmias. The problems are analysed on a set of records taken from MIT-BIH Arrhythmia Database from PhysioNet web portal (Goldberger et al., 2000; Moody et al., 2001). The three main objectives of the present review are as follows:

- 1 to summarise the studies related to ECG classification by ANN and SVM classifiers
- 2 to present the studies related to ECG signals classification using swarm optimisation algorithms (SOAs)
- 3 to introduce an ECG signal classification based on water wave optimisation (WWO) optimised SVM.

The remaining part of this paper contains following five sections: ECG signal are described in Section 2. Methods are described in Section 3. The Section 4 provides proposed ECG classification model based on WWO optimised SVM. Experimental results are highlighted in Sections 5. Section 6 provides the conclusion arrived by this paper.

2 ECG signal

Data from the MIT-BIH arrhythmia database, which was provided by the Massachusetts Institute of Technology (MIT) and the Boston Hospital (BIH) in 1987 (<http://www.physionet.org/physiobank/database/mitdb/>) (Goldberger et al., 2000; Moody et al., 2001), was utilised in most of the research studies. The database is taken for one of the mainstream databases in discovering and clustering arrhythmias and has been utilised in great number for algorithm verification. An annotation file with each recording is presented by the MIT-BIH arrhythmia database, preparing the reference for each heartbeat e.g., the category and the heartbeat locations. The category annotation is utilised as the criterion for the classified results. The manual annotation of the heartbeat locations, placed at the R-wave peak or the major local extrema, is utilised for segmenting ECG signals. There are six known types of beats to be identified; normal beat, premature ventricular contraction (PVC), Fusion of ventricular and normal beat (F), atrial premature beat (A), right bundle branch block beat (R) and fusion of paced and normal beat (f). Each heartbeat can be accurately described by an ECG wave form consisting of five peaks (features). Those peaks are known as P, T, Q, S and R. The detection and evaluation of every single peak and their variances, distances and other mathematical characteristics leads to a powerful identification of heart beat properties. As a part of ECG automatic detection process, additional features such as energy and entropy of the ECG signals are extracted from P, Q, R, S and T wave forms as feature vectors. P, Q, R, S, and T waves are representing a set of values describing the amplitudes and relative time intervals of ECG heartbeat wave as shown in Table 1.

Table 1 ECG waveform parameters

<i>Amplitude (mV)</i>	<i>Duration (seconds)</i>
P Wave – 0.25mV	PR interval – 0.12s to 0.20s
R Wave – 1.60mV	QT interval – 0.35s to 0.44s
Q Wave – 25% of R wave	ST interval – 0.05s to 0.15s
T Wave – 0.1 to 0.5mV	QRS interval – 0.09s

3 Preliminaries

ECG heartbeat classification techniques is partition into four parts, namely; pre-processing, feature extraction, feature selection and classification.

- 1 In the pre-processing stage, several kinds of noises are removed from the original input raw ECG signals.
- 2 In the feature extraction stage, standardisation and projection matrix are applied to each heartbeat, and a morphological descriptor of the heartbeat is represented in a lower dimension space. Besides, dynamic information about the heartbeat is represented by a set of weighted R-R intervals.
- 3 In the feature selection stage, only selection of relevant features is done.
- 4 In classification stage, the classifier is applied for final-heartbeat classification.

Numerous methodologies for automatic diagnosis have been proposed in researches. Signal acquisition, artefacts elimination, thresholding, and signal enhancement are main activities of pre-processing stage. Accuracy of signal acquisition is of great importance since it contributes significantly to the overall classification result. Feature selection is an optional stage, whereby the feature vector is reduced in size including only, from the classification viewpoint, what may be considered as the most relevant features required for discrimination. Classification stage is the final stage in automated diagnosis. It examines the input feature vector and based on its algorithmic nature, produces a suggestive hypothesis.

3.1 ECG signal pre-processing

Pre-processing of raw ECG signals is indispensable to reduce various noises, such as baseline drift, power-line interference, and high-frequency noises owing to muscle contractions and electrode movements, which can disturb the fiducial point detection and heartbeat classification and contributes significantly to the overall classification result. The baseline wander modification and noise reduction of ECG signals always applies a wavelet-based approach.

De-noising is an important issue for the analysis of signals as a first pre-processing stage. It targets some signal artefacts that are the power line interference, baseline wandering effect, and muscle noise. Muscle noises are generated due to some muscle contractions and side motions where an interference voltage generated whenever a patient contracts a body muscle. These micro-voltages are detected by the electrode and shown in the signal as noise. The power-line interference is caused by the electromagnetic field

interfering with the ECG equipment cables. Other sources due to electrode contact noise. Baseline wandering effect causes the entire ECG signal to shift up or down from the normal-base at zero y-axis.

Filtering signal noises is always done by means of **filtering techniques** such as high-pass filter, low-pass filter, notch filter, FIR smoothing filter (Li et al., 2014) and adaptive filtering (Douglas, 1999) and Hamilton and Tompkins algorithm (Hamilton and Tompkins, 1986). Finally, Kærgaard et al. (2016) have used discrete wavelet transform (DWT) combined with the neural network (NN), named the wavelet NN (**WNN**) for denoising the ECG signals.

3.2 Feature extraction

The second stage is feature extraction. It aims to finding a set of relevant features of ECG data that can attain the best classification accuracy performance and provide a significant contribution in diagnosing lots of cardiac diseases. Feature extraction is simply the determination of a feature or a feature vector from a pattern vector. In order to make pattern processing problems, solvable one needs to convert patterns into features, which become condensed representations of patterns, ideally including only prominent information.

Feature extraction methods, including principal component analysis (PCA), independent component analysis (ICA), wavelet transform (WT), and Gabor wavelet analysis (Afrin, 2014), etc. have been introduced for the same purpose. Feature extraction methods could be based on either calculating statistical characteristics or producing syntactic descriptions. The feature selection process ordinarily is designed to provide a means for choosing the features which are best for classification optimised (Padhy and Dandapat, 2017). In ECG signals, one cardiac cycle in an ECG signal includes of the P-QRS-T waves. This feature extraction technique determines the amplitudes and intervals in the ECG signal for subsequent analysis.

During feature extraction process, a feature vector from each heartbeat is calculated. There are a number of features that are known to be effective in ECG classification concerning the amplitudes and intervals value of P-QRS-T heartbeat segment which shape decides the operation of the heart of every human. Recently, numerous research and techniques have been presented for analysing the ECG based on the QRS complexes, RR intervals, ST segments, and other combinations of P, Q, R, S and T heartbeat wave peaks. A large number of features have been introduced in literature to describe the EEG signals.

Finding the right feature combinations is a significant task. However, if all known features are to be considered, it would be considered too large to be processed and it would result in a heavy computational cost. Also some features are proven to be useless for describing some cardiac diseases. A feature selection process is required to identify features that are most descriptive for a particular type of disease (Ye et al., 2012). Table 2 presents some review of the literature in which are proposed at this point.

Table 2 Summary of the published algorithms

<i>Studies</i>	<i>Feature extraction</i>	<i>Classifier</i>
Banerjee and Mitra (2014)	ICA and RR intervals	Sparse repression-based classifier
Adam et al. (2014)	Wavelet and spectral	Threshold-based classifier
Zhang et al. (2014)	Waveform and HOS	Conditional random field
Ye et al. (2012)	Wavelet and RR intervals	Evolutionary ANN
de Lannoy et al. (2012)	Wavelet and ICA	SVM
Huang et al. (2012)	Waveform and RR intervals	Dynamic Bayesian network
de Oliveira et al. (2011)	Wavelet and ICA	SVM
Ince et al. (2009)	Hermite and RR intervals	Block-based NN
Jiang and Kong (2007)	Waveform and RR intervals	Linear discriminates
de Chazal and Reilly (2006)	Waveform and RR intervals	Linear discriminates
Rodriguez et al. (2005)	Waveform	Decision tree
Osowski et al. (2004)	HOS and Hermite	SVM
Prasad and Sahambi (2003)	Wavelet and RR intervals	NN

3.3 Feature selection/optimisation

Selecting most relevant feature set for maximum classification accuracy and performance can be identified as an optimisation problem. Recent research efforts applied optimisation techniques for the sake of feature selection to optimise or reduce the number of features and eliminate redundant, noisy or irrelevant ones (Hassanien and Emary, 2016; Emary et al., 2015). Furthermore, the classification often becomes more accurate when the pattern is simplified by including important features or properties only.

The feature selection process performed on a set of predetermined features. Features are selected based on either best performance of a given class of signals, or best distinction between classes. Therefore, feature selection represents a significant role in classifying systems such as NNs. For the purpose of classification problems, the classifying system has usually been implemented with rules using if-then clauses, which state the conditions of particular attributes and resulting rules. However, it has proven to be a difficult and time-consuming method. From the viewpoint of achieving large quantities of data, it would still be most useful if irrelevant or redundant attributes could be segregated from relevant and important ones, although the exact controlling rules may not be known. In this case, the process of extracting useful information from a large data set can be greatly facilitated using **SOAs** (Hassanien and Emary, 2016; Mahmoodabadi et al., 2015).

Some researchers have introduced the application of **PSO** a technique for feature and classifier parameter optimisation (Daamouche et al., 2012; Korürek and Dögan, 2010; Melgani and Bazi, 2008). Further, these efforts proposes a technique for feature optimisation using firefly algorithm (FFA) and presents the classifier parameter optimisation approach (Kora and Krishna, 2016). In Ebrahimzadeh et al. (2014), authors have proposed hybrid bees algorithm-radial basis function (RBF-BA) technique is used to classify the five types of ECG beat. In Pham et al. (2007), authors introduced a technique for feature optimisation using bees algorithm (BA) and present the classifier parameter

optimisation approach. Also a technique for feature optimisation using cat swarm optimisation algorithm (CSOA) and classifier parameter optimisation appeared in Abed (2015).

3.4 Classification

Different types of classification techniques are used to classify ECG data under the extracted features and with the help of SOAs. The ECG beats after segmentation is re-sampled. It contains one or more classifier units which select one of the required classes in response to the input feature vector. Consequently, going through the last classification step, ECG signals representing heart beats are classified into either normal beats or abnormal beats (representing cardiac arrhythmia). If arrhythmia could be detected early, patients can be appropriately treated with proper medication and care. There is a number of types of arrhythmias that are well-known by specialists and can be classified using classification techniques. Arrhythmias include left bundle branch block (LBBB), normal sinus rhythm (NSR), ventricular tachycardia (VT), pre-ventricular contraction (PVC), atrial premature contraction (APC), and supraventricular tachycardia (SVT). Classification process of ECG signals utilises many classification techniques such as ANN (Silipo and Marchesi, 1996), fuzzy logic system (Tsipouras et al., 2007), linear discriminant analysis (LDA) and SVM. SVM and ANN have gained attention by most researchers for CVDs classification based on ECG signals (Ghosh et al., 2005). There are few research efforts apply evolutionary classifiers in this field. In the next sub-sections, we will present different classifiers for ECG heartbeats.

3.4.1 Support vector machines

Previous research efforts showed a great performance of SVM classifier. It employs a data representation technique over a P-dimensional vector (Karpagachelvi et al., 2012; Wu and Zhou, 2006). Classification is obtained by means of optimal separating hyper-planes (OSH) which aim to achieve the greatest margin between closest data points that belong to separate classes. SVMs depend on kernel functions in classification process. Kernel choice greatly affect the classification performance which is considered a significant task.

The greatest data separation margin is represented by a separating hyper-plane that separates positive and negative classes in a two-class problem. The following set of equations describes how to obtain the separation hyper-plane, with symbols described in Table 3.

$$f(x) = (w \cdot \phi(x)) + b \quad (1)$$

$$R_{SVM}(c) = c \frac{1}{N} \sum_{i=1}^N L_{\epsilon}(y_i y_i^A) + \frac{1}{2} W^T \cdot W \quad (2)$$

$$L_{\epsilon}(y_i y_i^A) = \begin{cases} |y_i - y_i^A| - \epsilon & \geq \epsilon \\ 0 & \text{Otherwise} \end{cases} \quad (3)$$

$$y^\Delta = f(x) = \sum_{i=1}^N (\alpha_i - \alpha_i^*) K(x_i, x) + b \quad (4)$$

$$K(x_i, x) = \exp\left(\frac{-1}{\delta^2} (x_i - x_j)^2\right) \quad (5)$$

Table 3 Symbols, equations (1) through (5)

Variable	Meaning
$\phi(x)$	The nonlinearity high dimension feature space which mapped from the input space x .
w :	The modifiable model parameter.
b	The threshold value.
$wandb$	Estimated by minimising.
$\alpha_i = \alpha_i^*$	The Lagrange multipliers, which are positive real constants. The data points identical to non-zero value for $(\alpha_i = \alpha_i^*)$ are called support vectors.
$k(x_i, x)$	The inner product kernel function (Gaussian Kernel).
δ^2	The Gaussian kernel factor (the width of the kernel function).
C	Positive real constant controls the trade-off between training error and generalisation ability and its value is chosen by means of a validation set.
ϵ	The parameter for SVMs.

SVM is a supervised ML method (Chang and Lin, 2011). SVM utilises structural risk minimisation (SRM) principle whereas in ANN, empirical risk minimisation (ERM) is utilised to minimise training data error. SVM performs classification tasks by constructing OSH and maximises the margin between the two nearest data points consistence with two separate classes. In the nonlinearly separable cases, the SVM maps training points to a high dimensional feature space based on kernel function which makes data separability more clear. The performance of SVM can be planned through the term C (SVM penalty) and kernel parameters. These parameters are of great influence on the number of the SVMs and the maximisation separation margin. The free parameters C and γ (gamma) extremely affect classification accuracy of SVM model. However, it is not known beforehand what values of the parameters are most suitable for given data. Therefore, as aforementioned in Section 3, SOAs are employed to search for better combinations of such parameters in SVM and can obtain the optimal solution after a set of iterative computations and heuristic search steps.

3.4.2 Artificial neural network

NNs are widespread and efficient tools for pattern recognition problems like ECG heartbeat classification. Many techniques have been introduced which are based on different NN structures (Ceylan et al., 2009). NN structure is famous according to its fast learning algorithms such as a radial basis-based neural network (RBFNN). RBFNN is nonlinear hybrid networks which are exactly containing a single hidden layer of neurons. The input layer forwards the coordinates of the input vector to each of the nodes in the hidden layer. Every node in the hidden layer then computes an activation according to the associated radial basis function (RBF). At the end, each node in the output layer

computes a linear combination of the activations of the hidden nodes (Ou et al., 2005). Figure 1 shows the general diagram of the RBFNN.

Figure 1 General structure of the RBF NN (see online version for colours)

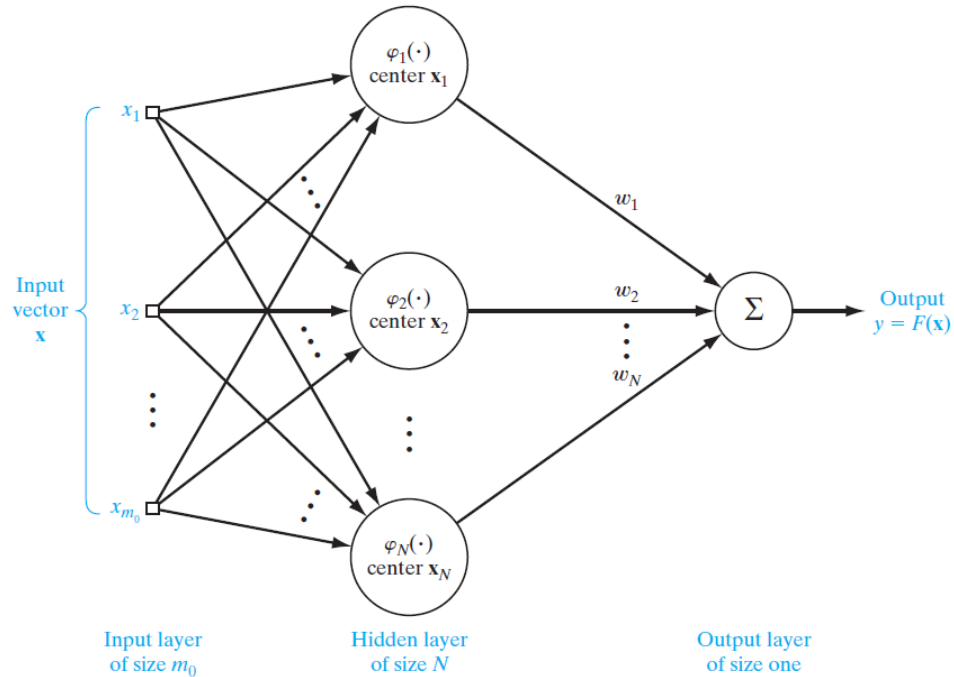


Table 4 Review of previous studies on the feature extraction and classification

<i>Studies</i>	<i>Techniques</i>	<i>Performance</i>
Shadmand and Mashoufi (2016)	Block-based neural network (BBNN)	97%
Kora and Krishna (2016)	Hybrid firefly and PSO with NN	FFPSO provided better results than firefly
Kora and Kalva (2015)	Bacterial foraging optimisation (BFO) and PSO with NN	BFPSO provides better results
Li et al. (2014)	SVM	80.26%
Adam et al. (2014)	PSO and random asynchronous	99.90%
Sambhu and Umesh (2013)	One against one (OAO) with SVM	97%
Moein and Logeswaran (2012)	PSO-NN	PSO-NN provided better results
Daamouche et al. (2012)	PSO-SVM	84.03%
Bakhshipour et al. (2010)	SVM	99.4% and 98.1%

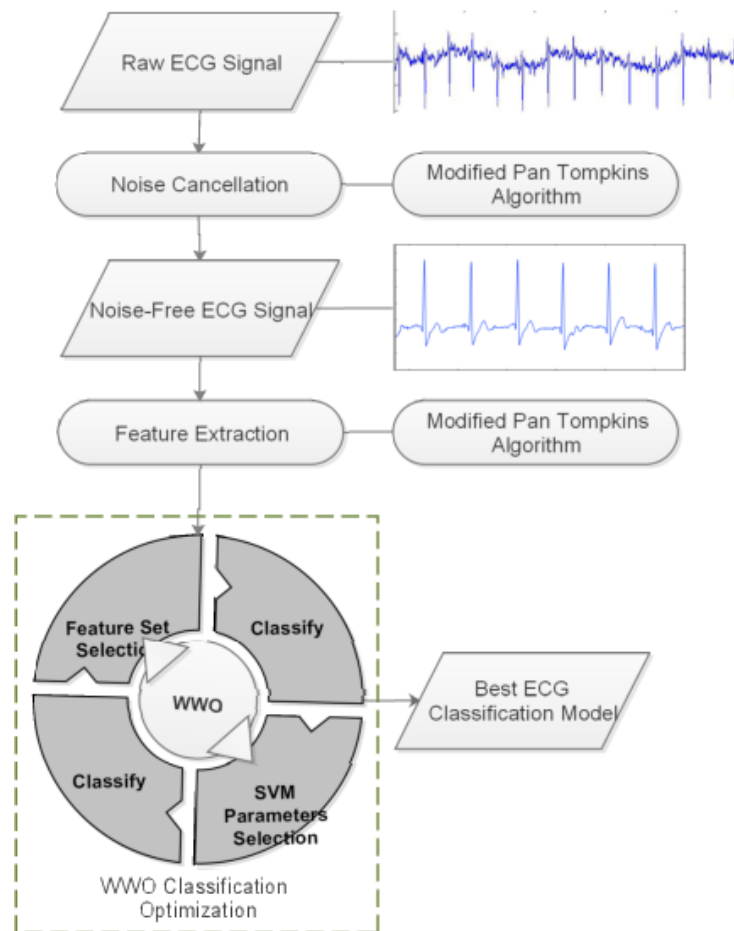
According to the previous discussion in Section 3.4, several algorithms have been developed in literature to improve the detection and classification of ECG signals. Better performance depends on features and the methods of classification. Table 4 shows a number of previous research classification. Table 4 shows each research effort reference, classifier have been applied and the performance of the classifier.

4 Proposed ECG Classification Approach

The proposed model is a hybrid system that employs **WWO** (Zheng, 2015) to fine-tune the classification model in terms of finding best feature set (feature selection) and the best SVM parameters. Three main stages are comprising the proposed approach;

- 1 pre-processing
- 2 feature extraction
- 3 classification and optimisation stage.

Figure 2 The proposed ECG classification optimisation model (see online version for colours)



Block diagram of the proposed model is demonstrated in Figure 2. The pre-processing stage consists of amplitude adjustment and filtering of ECG signals. The ECG signals are normalised to a mean of zero and standard deviation of identity, that way decreasing the amplitude variance from file to file. The embedded noises in ECG signals are separated frequency of 4–22 Hz using a band-pass filter. The pre-processed ECG signal is utilised in next stage for extracting significant features. The R peaks of ECG signals are situated utilising the annotated file of MIT-BIH database.

In this paper, WWO was modified for the purpose of classification optimisation. Waves locations are identified as SVM parameters and selected features set, while wave fitness is realised as the average classification accuracy over all cross validation folds which are three folds in this paper. Algorithm 1 shows the algorithmic framework of WWO-SVM classifier that was presented in Figure 2.

Furthermore, wave fitness represents average classification accuracy of cross validation folds (Three folds in this paper). At each wave evaluation (objective evaluation), SVM is trained and tested using three training data folds and three validation folds respectively. Algorithm 2 shows the objective function calculation with the help of SVM classifier.

4.1 Pre-processing

The modified Pan-Tompkins algorithm (MPTA) (Pan and Tompkins, 1985; Kritika Bawa, 2014) consists of derivative, moving average, squaring and threshold operations. MPTA follow these steps: first of all there is a band-pass filter which is composed of low pass and a high pass filter and it reduces noise. After this a derivative filter is used in order to get the slope information. After that an amplitude squaring is done and then the signal is passed to a moving-window integrator. Then thresholding is done to locate R-peaks.

Algorithm 1 Proposed ECG classification approach

```

1   Output: Accuracy measures
2   Initialise population
3    $W_{best} \leftarrow RandomWaveLocation$ 
4   for  $G \leftarrow 1$  to  $GenerationsCount$  do
5       for  $W \leftarrow 1$  to  $WavesCount$  do
6           WWO move W to new location  $Loc(W^*) = SVM\ Parameters + Features\ Set.$ 
7           WWO Evaluate_Fitness at  $Loc(W^*)$  (Algorithm 2).
8       end for
9       if then  $Fitness(W^*) > FitnessW_{best}$   $W_{best} = W^*$ 
10      end if
11  end for
12  Get Accuracy Measures for  $W_{best}$ 
13  EXIT

```

Most of ECG signals include noise. These noises are because of the environmental situation or circumstances during recording the signals and AC power swinging. Removal of different kinds of artefacts from the ECG signal is the main objective of the pre-processing. ECG signal is affected by a different kinds of noise which require different strategies. In this paper, MPTA is used to remove different kinds of artefacts and noises. First of all, there is a band-pass filter which is composed of low pass and a high pass filter and it decreases noise. Moreover, a derivative filter is used in order to get the slope information. Furthermore, an amplitude squaring is done and then the signal is passed to a moving window integrator. Finally, a thresholding technique is applied and the peaks are detected.

Algorithm 2 Evaluate wave fitness

```

1   Input: training sets ( $T_1, T_2, \dots, T_n$ )
2   Input: validation sets ( $V_1, V_2, \dots, V_n$ )
3   Input:  $Params \leftarrow$  Classification parameters (wave location)
4   Output: classification fitness
5   for each training set  $T_i \in T_1, T_2, \dots, T_n$  do
6       Train SVM on  $T_i$  using  $Params$ 
7       Validate training on  $V_i$ 
8        $Acc \leftarrow Acc + ValidationAccuracy$ 
9   end for
10   $TotalAccuracy \leftarrow Acc/n$ 
11   $Fitness \leftarrow TotalAccuracy$ 
12  EXIT

```

4.2 Feature extraction

QRS complex was detected using MPTA on the de-noised ECG signal. The algorithm consists of derivative, moving average, squaring and threshold operations. The derivative provides slope information, moving average operations eliminates the high-frequency noise in the signal, squaring operation enhances higher peaks, suppresses minimal amplitudes, and threshold operation produces rectangular pulses, at the center of the QRS complex. After the detection of QRS mid-point, the ECG data was segmented such that each segment comprises of 99 samples before QRS mid-point, 100 samples after QRS mid-point. Each of these 200 samples of ECG beats of five classes was utilised for this paper.

In order to perform feature extraction, a wave analysis technique is mandatory. Wave analysis techniques tend to decompose a given wave into its building blocks of wavelets. Some wave analysis techniques are Fast Fourier Transform (FFT), DWT, Auto Regressive approaches, and others. ECG signals are usually varying from individual to individual, the specific waveform components, such as P-wave, the QRS-complex and the T-wave, will have different properties for different individuals. ECG signal of different cardiac disease generates distinct patterns in the time-frequency domain. Research suggests numerous features sets be extracted and selected for classification such as the RR interval, which is utilised in most studies. It can be said that every single study discusses a new set of features to be used, or a new combination of existing ones. In this

paper, the ECG signal parameters are extracted from the QRS complex, the ST segment, and the statistical properties of the signal using the MPTA.

4.3 Classification and optimisation

The proposed approach uses WWO for the feature selection and parameters optimisation of SVM to improve classification accuracy. Research efforts showed dependency between feature optimisation and SVM parameters optimisation. A known approach is to perform.

4.4 Objective function

The optimisation algorithm generally depends on its fitness function to obtain the best solution. In this paper, the classification accuracy is chosen as the solution qualifier through the search process. Classification accuracy is between the range [0, 1], each wave (search agent) reflects a number of accuracies depend on cross validation strategy. Moreover, each wave reflects three accuracy values for each fold and all accuracy values for all folds are averaged to return fitness value to the search algorithm as illustrated in equation (6).

$$f(i, j) = \left(\sum_{k=1}^n Acc_{i,j,k} \right) / n \quad (6)$$

where $f(i, j)$ is the fitness value for elephant i in iteration j . n represents the number of folds selected for cross validation. $Acc_{i,j,k}$ is the resultant accuracy of evaluation for elephant i in iteration j and for the data fold k .

5 Experimental results and discussion

In order to estimate the performance of the proposed approach, input ECG data is split to training and test sets, then k-fold cross-validation (leave one out) was applied subsequently (Zweig and Campbell, 1993). In this paper, the value of k is set to 3; hence, ECG dataset was divided into three distinct parts. Two parts are used to train the classifier, while the third part (which is unseen by the classifier) is used to test classification. The proposed approach implemented the one-against-all multi-class SVM system to fine-tune the SVM parameters and feature set selection, parameter selection setting for SVM, kernel parameters are determined. Gaussian RBF is applied in this paper.

5.1 ECG dataset description

Researchers have been using standard databases for analysis purposes. The PhysioNet website is dedicated for medical data corresponding to various diseases. PhysioNet databases are built up of hundreds of medical records for digitised ECG, EEG and other types of signals. Each ECG record is annotated and revised by a number of cardiologists. Many research efforts depend on MIT-BIH arrhythmias database provided by PhysioNet.

It consists of several ECG signal records for patients that indicate different types of diseases and abnormalities of the heart rhythms (Korurek and Nizam, 2010).

The MIT-BIH Arrhythmia Database contains 48 half-hour records obtained from 25 male and 22 female subjects studied by the MIT-BIH Arrhythmia Laboratory. The recordings were digitised at 360 samples per second per channel with 11-bit resolution over a 10 mV range. Two or more cardiologists independently annotated each record; disagreements were resolved to obtain the computer-readable reference annotations for each beat (approximately 110,000 annotations in all) included with the database (Korurek and Nizam, 2010). Our experiment conducted on the basis of ECG data (ten patients), Table 5 displays the datasets employed in our experiment.

Table 5 ECG dataset description

<i>N</i>	<i>Patient number</i>	<i>Gender</i>	<i>Age</i>	<i>PhysioNet standard beat types</i>
1	202	Male	68	N-A-a-V-F
2	203	Male	43	N-a-V-F
3	205	Male	59	N-A-V-F
4	207	Female	89	L-R-A-V-E
5	214	Male	53	L-V-F
6	215	Male	81	N-A-V-F
7	217	Male	65	N-V-/-f
8	219	Male	Unknown	N-A-V-F
9	221	Male	83	N-V
10	223	Male	73	N-A-a-V-F-c

5.2 Performance metrics

There is numerous performance measures concerning classification results in general. Five metrics take the first place in literature which are:

- 1 the accuracy (Ac), representing the percentage of how much correctly classified beats through all the beats considered (independently of the classes they fit to)
- 2 specificity (Sp), it stands for the fraction of beats that has been correctly rejected
- 3 F-measure
- 4 precision
- 5 recall.

These measures have been used to evaluate the performance of the classifier. Performance measures, in general, depend on four main metrics of a binary classification result (positive/negative); true positive (TP), true negative (TN), false positive (FP), false negative (FN), where A true statement states that the predicted class is correct whilst a positive statement corresponds to a predicted class to be positive, False and Negative letters have got the opposite meanings respectively. Performance measures are defined in the following equations. accuracy (Ac): overall accuracy of the classifier has been defined as:

$$\text{Acc} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}} * 100 \quad (7)$$

Specificity (Sp), also known as true negative rate, measures the proportion of negative predictions that are correctly identified as negative:

$$\text{Sp} = \frac{\text{TN}}{\text{TN} + \text{FP}} * 100 \quad (8)$$

Recall known as the true positive rate (TPR) or sensitivity (Se), measures the proportion of positives that are correctly identified as positive.

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}} * 100 \quad (9)$$

Precision, known as positive predictive value (PPV), is the fraction of retrieved instances that are relevant.

$$\text{PPV} = \frac{\text{TP}}{\text{TP} + \text{FP}} * 100 \quad (10)$$

F-measure, the harmonic mean of precision and recall.

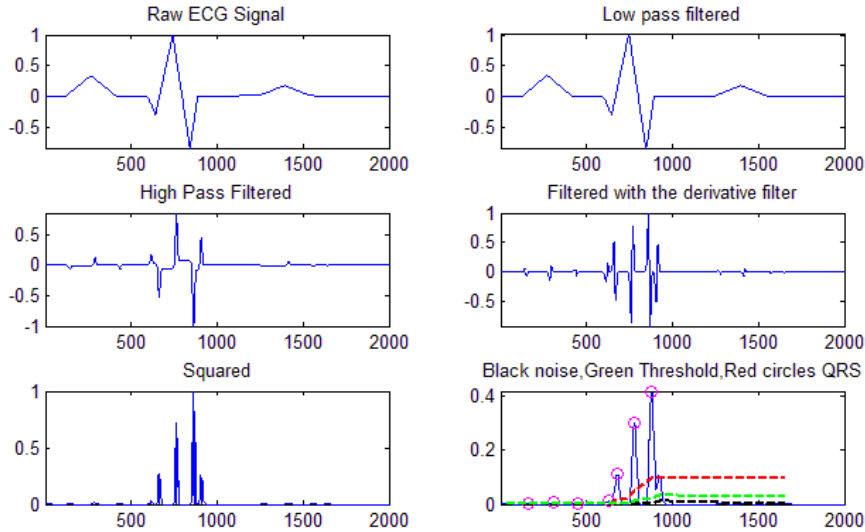
$$F = 2 * \frac{\text{PPV} * \text{TPR}}{\text{PPV} + \text{TPR}} \quad (11)$$

The case study being solved in this research is not binary, so we employ a confusion matrix to express the TP, FP, TN, and FN measures constructed for a classification test. Confusion matrix can easily produce all five performance metrics discussed before.

5.3 Experimental results

MPTA is used to remove different kinds of artefacts and noise. The noise of ECG signal contains power line interference, baseline wandering effect, and muscle noise. MPTA is used to remove different kinds of artefacts and noise. Figure 3 shows common noise of raw ECG signals. In this paper, the ECG signal parameters are extracted from the QRS complex, the ST segment, and the statistical characteristics of the signal using MPTA. MPTA in this research was employed to extract nine heartbeat wave characteristic features that are shown in Table 6. As aforementioned, many research efforts suggested different features are extracted from the nine features set described in Table 6 is calculated using MPTA.

We have chosen ten patients that define a considerably sufficient number of beat types in order to make classification results more valid and describe several types of heartbeats. Table 7 summarises for each patient record along with classification accuracy, precision, recall, F-measure, specificity abbreviated to Acc, Prec, Rec, F, and Spec respectively. Table 7 shows the accuracies obtained on the test beats by feeding the SVM classifier based on WWO with the features generated by the proposed approach.

Figure 3 Step by step output of MPTA (see online version for colours)**Table 6** Nine heartbeat wave features by MPTA

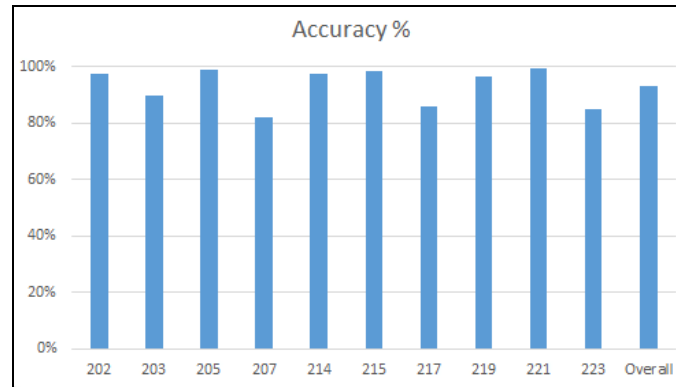
<i>N</i>	<i>Features</i>	<i>Meaning</i>
1	PS	The beginning location of P wave form
2	P	The peak location of P wave form
3	PE	The end location of P wave form
4	Q	The beginning of QRS complex
5	R	The R peak of QRS complex
6	S	The End of QRS complex
7	TS	The beginning of T wave form
8	T	The peak of T wave form.
9	TE	The end of T wave form

Table 7 Classification results

<i>Patient</i>	<i>Acc%</i>	<i>Prec%</i>	<i>Rec%</i>	<i>F%</i>	<i>Spec%</i>
202	97.28%	49.52%	34.03%	38.59%	86.49%
203	89.86%	23.94%	20.76%	20.51%	80.82%
205	98.79%	47.77%	45.12%	45.92%	92.31%
207	82.03%	32.26%	26.17%	26.64%	83.52%
214	97.49%	63.24%	60.89%	61.86%	96.95%
215	98.69%	32.90%	33.33%	33.11%	75.00%
217	85.77%	70.30%	70.34%	70.06%	94.75%
219	96.65%	48.55%	46.85%	47.44%	94.77%
221	99.42%	98.57%	99.34%	98.88%	99.35%
223	85.05%	27.63%	26.37%	26.33%	91.50%

Figure 4 shows the results for each record and the visual comparison between the best results obtained for each patient. In general, as can be observed from 4, these results show the superiority of the proposed approach has achieving a classification accuracy 99.42% and the overall classification accuracy for all records is 93%.

Figure 4 Experimental results (see online version for colours)



5.4 Comparison analysis

For comparison we have considered two previous works which have used the same data set. In Kora and Kalva (2015) tested MIT-BIH arrhythmia database using particle swarm optimisation (PSO), genetic algorithm (GA), bacterial forging optimisation (BFO), bacterial forging-particle swarm optimisation (BFPSO) with SVM. In Yochum et al. (2016), QRS, T and P waves delineation method is proposed. This algorithm is performed with the CWT and the histogram representation to determine a mask selection of the QRS, T and P waves. This comparisons are shown in Table 8.

Table 8 Comparison of results and methods with other studies which used same dataset

<i>Studies</i>	<i>Approach</i>	<i>Accuracy</i>
Daamouche et al. (2012)	PSO-SVM	84.03%
Li et al. (2014)	SVM	80.26%
Kora and Kalva (2015)	BFPSO-SVM	76.74%
Yochum et al. (2016)	Delineation method	92.44%
Proposed approach	WWO-SVM	93%

ECG signal carries some vital information about the heart and it is part of the principal tools for the doctors for diagnosing heart-related diseases. A lot of work has been presented by various researchers to extract the features from the ECG signal so that the analysis of ECG become automate and easier. Analysis of ECG signal depends upon accurate detection of various features of the ECG signal. In this paper, some of the principal algorithms of ECG feature extraction, feature selection and classification in prior research efforts has been introduced. The proposed approach including three modules: an efficient preprocessing module, feature extraction module, and classification for an automatic ECG signal classification. MPTA algorithm was employed for signal

pre-processing as well as feature extraction. In feature extraction module, MPTA algorithm is utilised to extract nine heartbeat features. Also, we have applied SVMs to classify features extracted from the previous module where WWO optimisation algorithm was employed to fine-tune SVMs parameters and input features set. As future work, we propose to automate the classification of cardiac arrhythmias using hybrid multilayer perceptron NN with a back propagation learning and bio-inspired optimisation techniques.

References

- Abed, M.A. (2015) 'New hybrid (SVMS-CSOA) architecture for classifying electrocardiograms signals', *International Journal of Advanced Research in Artificial Intelligence*, Vol. 4, No. 5, pp.30–36.
- Adam, A., Shapiai, M.I., Tumari, M.Z.M., Mohamad, M.S. and Mubin, M. (2014) 'Feature selection and classifier parameters estimation for EEG signals peak detection using particle swarm optimization', *The Scientific World Journal*, Vol. 13, pp.1–13.
- Afrin, K. (2014) 'Classification and feature extraction of binucleate cells using Mahalanobis distance and Gabor wavelet analysis', *International Journal of Intelligent Engineering Informatics*, Vol. 2, No. 4, pp.304–324.
- Alonso-Atienza, F., Morgado, E., Fernandez-Martinez, L., García-Alberola, A. and Rojo-Alvarez, J.L. (2014) 'Detection of life-threatening arrhythmias using feature selection and support vector machines', *IEEE Transactions on Biomedical Engineering*, Vol. 61, No. 3, pp.832–840.
- Bakhshipour, A., Pooyan, M., Mohammadnejad, H. and Fallahi, A. (2010) 'Myocardial ischemia detection with ECG analysis, using wavelet transform and support vector machines', *17th Iranian Conference of Biomedical Engineering (ICBME)*, IEEE, November, pp.1–4.
- Banerjee, S. and Mitra, M. (2014) 'Application of cross wavelet transform for ecg pattern analysis and classification', *IEEE Transactions on Instrumentation and Measurement*, Vol. 63, No. 2, pp.326–333.
- Ceylan, R., Özbay, Y. and Karlik, B. (2009) 'A novel approach for classification of ECG arrhythmias: type-2 fuzzy clustering neural network', *Expert Systems with Applications*, Vol. 36, No. 3, pp.6721–6726.
- Chang, C.-C. and Lin, C.-J. (2011) 'LIBSVM: a library for support vector machines', *ACM Transactions on Intelligent Systems and Technology*, Vol. 2, No. 3, p.27.
- Daamouche, A., Hamami, L., Alajlan, N. and Melgani, F. (2012) 'A wavelet optimization approach for ECG signal classification', *Biomedical Signal Processing and Control*, Vol. 7, No. 4, pp.342–349.
- de Chazal, P. and Reilly, R.B. (2006) 'A patient-adapting heartbeat classifier using ecg morphology and heartbeat interval features', *IEEE Transactions on Biomedical Engineering*, Vol. 53, No. 12, pp.2535–2543.
- de Chazal, P., O'Dwyer, M. and Reilly, R.B. (2004) 'Automatic classification of heartbeats using ecg morphology and heartbeat interval features', *IEEE Transactions on Biomedical Engineering*, Vol. 51, No. 7, pp.1196–1206.
- de Lannoy, G., François, D., Delbeke, J. and Verleysen, M. (2012) 'Weighted conditional random fields for supervised interpatient heartbeat classification', *IEEE Transactions on Biomedical Engineering*, Vol. 59, No. 1, pp.241–247.
- de Oliveira, L.S.C., Andreão, R.V. and Sarcinelli-Filho, M. (2011) 'Premature ventricular beat classification using a dynamic bayesian network', *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, IEEE, pp.4984–4987.
- Douglas, S.C. (1999) *Introduction to Adaptive Filters. Digital Signal Processing Handbook*, pp.7–12, CRC Press LLC, Boca Raton.

- Ebrahimzadeh, A., Shakiba, B. and Khazaei, A. (2014) 'Detection of electrocardiogram signals using an efficient method', *Applied Soft Computing*, Vol. 22, pp.108–117 [online] <http://www.sciencedirect.com/science/article/pii/S1568494614002191>.
- Emary, E., Zawbaa, H.M., Grosan, C. and Hassenian, A.E. (2015) 'Feature subset selection approach by gray-wolf optimization', *Afro-European Conference for Industrial Advancement*, Springer, pp.1–13.
- Ghosh, D., Midya, B.L., Koley, C. and Purkait, P. (2005) 'Wavelet aided SVM analysis of ECG signals for cardiac abnormality detection', *Annual IEEE India Conference-Indicon*, IEEE, pp.9–13.
- Goldberger, A.L., Amaral, L.A.N., Glass, L., Hausdorff, J.M., Ivanov, P.C., Mark, R.G., Mietus, J.E., Moody, G.B., Peng, C.K. and Stanley, H.E. (2000) 'Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals', *Circulation*, Vol. 101, No. 23, pp.e215–e220 [online] <https://physionet.org/physiobank/database/> (accessed August 2016).
- Hamilton, P.S. and Tompkins, W.J. (1986) 'Quantitative investigation of qrs detection rules using the mit/bih arrhythmia database', *IEEE Transactions on Biomedical Engineering*, Vol. BME-33, No. 12, pp.1157–1165.
- Hassanien, A.E. and Emary, E. (2016) *Swarm Intelligence: Principles, Advances, and Applications*, CRC Press, Taylor & Francis Group, Boca Raton.
- Huang, C.L. and Wang, C.-J. (2006) 'A GA-based feature selection and parameters optimization for support vector machines', *Expert Systems with Applications*, Vol. 31, No. 2, pp.231–240.
- Huang, H.F., Hu, G.S. and Zhu, L. (2012) 'Sparse representation-based heartbeat classification using independent component analysis', *Journal of Medical Systems*, Vol. 36, No. 3, pp.1235–1247, 2012.
- Ince, T., Kiranyaz, S. and Gabbouj, M. (2009) 'A generic and robust system for automated patient-specific classification of ECG signals', *IEEE Transactions on Biomedical Engineering*, Vol. 56, No. 5, pp.1415–1426.
- Jiang, W. and Kong, S.G. (2007) 'Block-based neural networks for personalized ECG signal classification', *IEEE Transactions on Neural Networks*, Vol. 18, No. 6, pp.1750–1761.
- Jovic, A. and Bogunovic, N. (2012) 'Evaluating and comparing performance of feature combinations of heart rate variability measures for cardiac rhythm classification', *Biomedical Signal Processing and Control*, Vol. 7, No. 3, pp.245–255.
- Kærgaard, K., Jensen, S.H. and Puthusserypady, S. (2016) 'A comprehensive performance analysis of EEMD-BLMS and DWT-NN hybrid algorithms for ECG denoising', *Biomedical Signal Processing and Control*, Vol. 25, pp.178–187 [online] <http://www.sciencedirect.com/science/article/pii/S1746809415001974>.
- Karpagachelvi, S., Arthanari, M. and Sivakumar, M. (2012) 'Classification of electrocardiogram signals with support vector machines and extreme learning machine', *Neural Computing and Applications*, Vol. 21, No. 6, pp.1331–1339.
- Kass, R.E. and Clancy, C.E. (2005) *Basis and Treatment of Cardiac Arrhythmias*, Vol. 171, pp. 1–40, Springer Science & Business Media, Springer-Verlag, Berlin Heidelberg.
- Kora, P. and Kalva, S.R. (2015) 'Hybrid bacterial foraging and particle swarm optimization for detecting bundle branch block', *SpringerPlus*, Vol. 4, No. 1, pp.1–19.
- Kora, P. and Krishna, K.S.R. (2016) 'Hybrid firefly and particle swarm optimization algorithm for the detection of bundle branch block', *International Journal of the Cardiovascular Academy*, Vol. 2, No. 1, pp.44–48.
- Korürek, M. and Dögan, B. (2010) 'ECG beat classification using particle swarm optimization and radial basis function neural network', *Expert Systems with Applications*, Vol. 37, No. 12, pp.7563–7569.
- Korurek, M. and Nizam, A. (2010) 'Clustering MIT-BIH arrhythmias with ant colony optimization using time domain and PCA compressed wavelet coefficients', *Digital Signal Processing*, Vol. 20, No. 4, pp.1050–1060.

- Kritika Bawa, P.S. (2014) 'R-peak detection by modified Pan-Tompkins algorithm', *International Journal of Advancements in Research & Technology*, Vol. 3, No. 5, pp.30–33.
- Kumar, S.U., Inbarani, H.H. and Azar, A.T. (2015) 'Hybrid bijective soft set-neural network for ECG arrhythmia classification', *International Journal of Hybrid Intelligent Systems*, Vol. 12, No. 2, pp.103–118.
- Li, Q., Rajagopalan, C. and Clifford, G.D. (2014) 'A machine learning approach to multi-level ECG signal quality classification', *Comput. Methods Prog. Biomed.*, December, Vol. 117, No. 3, pp.435–447.
- Mahmoodabadi, M.J., Taherkhorsandi, M., Maafi, R.A. and Castillo-Villar, K.K. (2015) 'A novel multi-objective optimisation algorithm: artificial bee colony in conjunction with bacterial foraging', *International Journal of Intelligent Engineering Informatics*, Vol. 3, No. 4, pp.369–386.
- Melgani, F. and Bazi, Y. (2008) 'Classification of electrocardiogram signals with support vector machines and particle swarm optimization', *IEEE Transactions on Information Technology in Biomedicine*, Vol. 12, No. 5, pp.667–677.
- Moein, S. and Logeswaran, R. (2012) 'Intelligent ECG signal noise removal using PSONN', *International Journal of Computer Applications*, May, Vol. 45, No. 6, pp.9–17.
- Moody, G.B., Mark, R.G. and Goldberger, A.L. (2001) 'Physionet: a web-based resource for the study of physiologic signals', *IEEE Eng Med Biol Mag*, Vol. 20, No. 3, pp.70–75.
- Osowski, S., Hoai, L.T. and Markiewicz, T. (2004) 'Support vector machine-based expert system for reliable heartbeat recognition', *IEEE Transactions on Biomedical Engineering*, Vol. 51, No. 4, pp.582–589.
- Ou, Y.-Y., Oyang, Y.-J. and Chen, C.-Y. (2005) 'A novel radial basis function network classifier with centers set by hierarchical clustering', *IEEE International Joint Conference on Neural Networks*, IEEE, Vol. 3, pp.1383–1388.
- Padhy, S. and Dandapat, S. (2017) 'Third-order tensor based analysis of multilead ECG for classification of myocardial infarction', *Biomedical Signal Processing and Control*, Vol. 31, pp.71–78 [online] <http://www.sciencedirect.com/science/article/pii/S174680941630088X>.
- Pan, J. and Tompkins, W.J. (1985) 'A real-time QRS detection algorithm', *IEEE Transactions on Biomedical Engineering*, Vol. BME-32, No. 3, pp.230–236.
- Pham, D.T., Afify, A. and Koc, E. (2007) 'Manufacturing cell formation using the bees algorithm', *Innovative Production Machines and Systems Virtual Conference*, Cardiff, UK.
- Prasad, G.K. and Sahambi, J.S. (2003) 'Classification of ECG arrhythmias using multi-resolution analysis and neural networks', *In TENCON 2003. Conference on Convergent Technologies for the Asia-Pacific Region*, IEEE, Vol. 1, pp.227–231.
- Rodriguez, J., Goni, A. and Illarramendi, A. (2005) 'Real-time classification of ECGs on a PDA', *IEEE Transactions on Information Technology in Biomedicine*, Vol. 9, No. 1, pp.23–34.
- Sambhu, D. and Umesh, A.C. (2013) 'Automatic classification of ECG signals with features extracted using wavelet transform and support vector machines', *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, Vol. 2, No. 1, pp.235–241.
- Shadmand, S. and Mashoufi, B. (2016) 'A new personalized ecg signal classification algorithm using block-based neural network and particle swarm optimization', *Biomedical Signal Processing and Control*, Vol. 25, pp.12–23 [online] <http://www.sciencedirect.com/science/article/pii/S1746809415001743>.
- Silipo, R. and Marchesi, C. (1996) 'Neural techniques for ST-T change detection', *Computers in Cardiology Conference*, IEEE, Indianapolis, IN, USA, pp.677–680.
- Tsipouras, M.G., Voglis, C. and Fotiadis, D.I. (2007) 'A framework for fuzzy expert system creation' application to cardiovascular diseases', *IEEE Transactions on Biomedical Engineering*, Vol. 54, No. 11, pp.2089–2105.
- Vapnik, V.N. (1995) *The Nature of Statistical Learning Theory*, Springer-Verlag New York, Inc., New York, NY, USA, ISBN 0-387-94559-8.

- Wu, Q. and Zhou, D-X. (2006) ‘Analysis of support vector machine classification’, *Journal of Computational Analysis & Applications*, Vol. 8, No. 2, pp.99–119.
- Ye, C., Vijaya Kumar, B.V.K. and Coimbra, M.T. (2012) ‘Heartbeat classification using morphological and dynamic features of ECG signals’, *IEEE Transactions on Biomedical Engineering*, Vol. 59, No. 10, pp.2930–2941.
- Yochum, M., Renaud, C. and Jacquir, S. (2016) ‘Automatic detection of p, qrs and t patterns in 12 leads ECG signal based on CWT’, *Biomedical Signal Processing and Control*, Vol. 25, pp.46–52, ISSN 1746-8094.
- Zhang, Z., Dong, J., Luo, X., Choi, K-S. and Wu, X. (2014) ‘Heartbeat classification using disease-specific feature selection’, *Computers in Biology and Medicine*, Vol. 46, pp.79–89 [online] <http://www.sciencedirect.com/science/article/pii/S001048251300348X>.
- Zheng, Y-J. (2015) ‘Water wave optimization: a new nature-inspired metaheuristic’, *Computers & Operations Research*, Vol. 55, pp.1–11 [online] <http://www.sciencedirect.com/science/article/pii/S0305054814002652>.
- Zweig, M.H. and Campbell, G. (1993) ‘Receiver-operating characteristic (roc) plots: a fundamental evaluation tool in clinical medicine’, *Clinical Chemistry*, Vol. 39, No. 4, pp.561–577.