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Analysis of QRS Detection Algorithm for Cardiac Abnormalities – a Review

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Abstract*— This work investigates and compares a set of efficient techniques to extract and select striking features from the ECG data applicable in automatic cardiac beat classification. Each method was applied to a pre-selected data segment from the MIT-BIH (Massachusetts Institute of Technology / Beth Isrel Hospital) database. The classification and optimization of different heart beat methods were performed based upon the extracted features (morphological and statistical feature). The morphological features were found as the most important for arrhythmia classification. However, because of ECG signal variability in different patients, the statistical approach is favoured for a precise and robust feature extraction. Among all these feature extraction, feature selection, classification and optimization techniques, SVM based PSO gives higher classification accuracy with curse of dimensionality.

***Index Terms*— Cardiac beat classifier, Feature Extraction, Feature Selection, SVM, PSO**

I. INTRODUCTION

A. Background

AUTOMATIC assessment of Cardiac Vascular Diseases (CVD) for patients has been a long time research; the cardiovascular disease is one of the leading causes of death around the world. The cause of CVD are due to the variations in the heart rate or irregularities and are characterized by the Electrocardiogram (ECG also known as EKG, abbreviated from the German *Elektrokardiogramm*) beats or patterns [1], [2]. The ECG signal is a representation of the bioelectrical activity of the heart representing the cyclical contraction and relaxation of the human heart muscles. To acquire the signal, ECG devices with varying number of electrodes (3– 12) can be used. Multi lead systems exceeding 12 and up to 120 electrodes are also available [3]. Accurate detection of the ECG beats is the key requirement for detecting CVD.

The Electrocardiogram (ECG) is a vital sign signal for heart functional investigation. This electric signal is generated from human heart to create the cardiac cycle, which generates the blood circulation. It is composed with three basic components
named P wave, QRS complex and T wave and it's Interval as show in Figure 1. P wave is generated during atrium depolarization. After that, QRS complex is generated during ventricular depolarization and T wave is generated when ventricle recovery occurs.

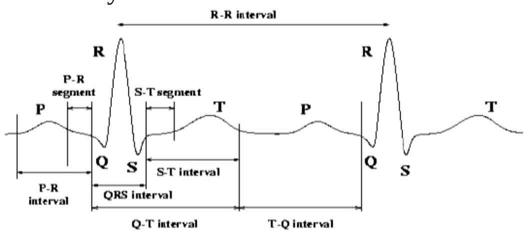

Fig. 1 ECG Intervals and Waves

This ECG is used clinically in diagnosing various abnormalities and conditions associated with the heart. The R-R interval is the distance between two subsequent QRS complexes and represents the Heart Rate (HR). Normal HR is between 60 to 100 beats per minute (bpm). A high HR means the possibility of tachycardia, and a low HR indicates sinus bradycardia Dieses.The amplitude and duration of normal ECG signal is tabulated below in Table.1

Table.1 Characteristics of ECG Waveform

Amplitude (mV)	Duration (Seconds)
P wave – 0.25mV	PR interval – 0.12 to 0.20 s
R wave – 1.60 mV	QT interval – 0.35 to 0.44 s
Q wave – 25% R wave	ST interval – 0.05 to 0.15 s
T wave – 0.1 to 0.5 mV	QRS interval – 0.09 s

During the recording process, noise heavily affects the signal. In addition, the ECG signals collected from different people are heterogeneous, generally reflected by the variations in the amplitude of the beats. Hence, computationally intensive preprocessing is required for beat detection and feature extraction. The most important features include the information lying in the P, Q, R, S, and T waves of the ECG signal [1]. ECG beats should be classified based on these features in order to detect different types of CVD. In ambulatory ECG, all kinds of noise may occur simultaneously and unpredictably.

Different kinds of noises [4] interfere with ECG signals are

- Baseline wandering,
- Electro Myo Gram (EMG) noise,
- Motion artefact,
- Power-line interference, and
- Electrode pop or contact noise.

ECG preprocessing generally takes care of denoising the ECG signal.

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Several works [5] have been done in the area of automatic ECG beat detection. Many commercial tools are available for automatic beat detection, but their performance is not satisfactory. In MATLAB the possible enhancements in other previous algorithms [2], [4] with the help of Wavelet Transforms [5] - [7] is done to reduce the complexity and to increase the SNR of the ECG signal before detection. The software application could take the ECG signal, denoise it, and perform the beat detection efficiently. Possible enhancements include reducing the number of fiducial marks (P, Q, R, S, and T waves) and reducing the number of thresholds that could, to a large extent, reduce the complexity.

After the preprocessing and beat detection, effective beat classification is required for correct analysis of different types of CVD [8]. The general trend is to develop automated systems to classify cardiac beats. This can significantly help to simplify the diagnosis of heart diseases. For example, heart-rate variability or diagnosis of certain arrhythmia (abnormal cardiac signal) may take up to several hours, when done by visual inspection. Even then, some vital information may be missed in between due to tedious manual procedure. Therefore, computer-based beat classification is essential and becoming the norm in clinical applications [2].So far, several techniques such as maximum likelihood, (artificial) neural networks [8], and support vector machines [9], [10] have been introduced for the ECG beat classification. These machine learning techniques map new data instances based on the information extracted from the annotated training data in the learning phase. Most techniques provide a global classifier that may not be always accurate for patient-specific cardiac variations. Automated arrhythmia-diagnosis systems that can provide high-classification accuracy rates for inter and intra-patient variation cases are still an active area of research.

B. Detection of localized abnormalities

Signal Averaged Eelectro CardioGram (SAECG) is a very specialized type of surface ECG, which involves computerized analysis of small segments of a standard ECG in order to detect abnormalities, termed as ventricular late potentials (VLP) which would otherwise be obscured by skeletal muscle and electrical noise. There are various types of these low amplitude signals which can be detected by SAECG [11], but the most important are VLP and the main clinical use of SAECG is to detect these VLPs. VLP are present in terminal part of QRS complex and these may extend into ST segment; hence called '*late potentials*' because these arise late in ventricular activation process.

Ventricular late potentials had been the pivotal point of cardiac electro physiologic research for the last twenty-five years and they have been investigated extensively. VLPs arise in an area of myocardium where the conduction velocity of cardiac impulse is slow, e.g., peri-infarct zone. This means when depolarization in healthy myocardium is complete or almost complete this area will still be depolarizing. It will lead to the generation of low voltage, fractionated signals towards the end of QRS complex. The same area will become substrate for the development of ventricular tachyarrhythmias through re-entry mechanism [12]. Therefore VLP may act as noninvasive marker for the development of ventricular tachyarrhythmias. The criteria for their presence and co-relation with ventricular tachyarrhythmias are now well established. Therefore identification of subjects prone to have high risk of developing ventricular arrhythmias is a major challenge for clinical research.

Non-invasive identification of patients at increased risk of developing malignant ventricular arrhythmias leading to sudden death remains a major challenge for the cardiovascular research. At present accurate prediction of patients at risk of developing ventricular tachyarrhythmias by the available non-invasive tests that is, electrocardiography and echocardiography are not promising. This necessitates looking into new tests which could correctly identify patients at risk of ventricular tachyarrhythmias. One such predictor of ventricular tachyarrhythmias, we used in our study is 'Ventricular Late Potentials' (VLP) which can be detected on signal averaged ECG. VLP have been studied extensively in patients with various cardiac pathologies.

II. MATERIALS AND METHODS

The ECG Beat Classification described in this paper will consist of 5 modules.

ECG (ventricular arrhythmia) signals used for the research were obtained from the Physionet Database (*Physio Bank*) [13]. A set of programs from the Physionet was used to import ECG records each of which consists of data file, attribute file and header file in Matlab. Matlab and its Wavelet toolbox were used for ECG signal processing and analysis.

1. Preprocessing Module: The ECG signals were preprocessed by filtering it to remove the baseline wander, the power line interference, and the high frequency noise, hence enhancing the signal quality, and omitting the equipment and the environmental effects.

2. Feature Extraction Module: This module is important in the post processing of ECG readings, because a good set of features will have sufficient discriminative power to facilitate the diagnosis or investigation.

3. Feature Reduction Module: With the help of appropriate Feature Reduction Technique the required feature for the classifier is selected.

4. Classifier and Optimizer Module: Supervised neural networks Classifier - Support Vector Machine based Particle Swarm Optimizer is preferred for its generalization capability.

5. Output module: Gives the performance metrics of the Analyzer and diagnosis result.

A. ECG Signal Pre-Processing

As for pre-processing of the ECG signal, noise cancellation requires different strategies for different noise sources. Thakor and Zhu [15] performed the noise reduction using an adaptive filter with constant or unity reference input, which was used to cancel baseline wander. However, this filter is not reliable for applications that require diagnostic ECG analysis.

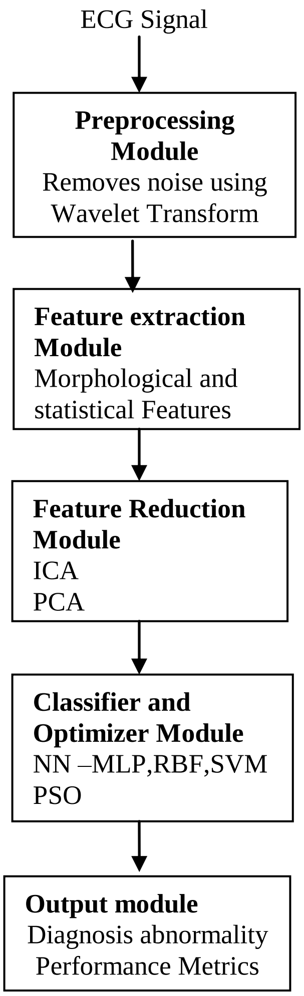

Fig.2 Flow Diagram of ECG Beat Classification

The baseline wandering and the power-line interference (hum noise) are the most substantial noises and can strongly affect the ECG signal analysis [5]. Baseline wandering (or trend) usually comes from respiration and lies between 0.15 and 0.3 Hz. Other than these two noise elements, the remaining is wideband and usually complex stochastic processes, which also distort the ECG signal and affect the analysis.

The power-line interference is a narrow-band noise centered at 60 Hz (or 50 Hz in Europe and some other countries) with a bandwidth of less than 1 Hz [4]. Usually, the ECG signal acquisition hardware can remove the power-line interference, but the baseline wandering and other wideband noise cannot be easily suppressed by hardware equipment without elaborate circuitry. However, software schemes can be used for ECG signal processing and suppression of these noise sources.

B. Feature generation / extraction Methodology

Extraction of various parameters or *features* is of paramount importance in automatic ECG beat classification. The term *parameter* or *feature* refers to the ECG waveform characteristics in an all encompassing sense. The important parameters derived from stochastic information and morphological metric analysis of normal and pathological ECG signals included in a database to distinguish between different types of abnormalities.

Nonlinear filtering is a common approach to detect QRS complexes [4] in considerably less time and can be easily implemented. However, the main drawback of these algorithms is the frequency variation in QRS complexes, which adversely affects their performance. These methods can result in higher false positives and false negatives during the detection process, because the frequency band of QRS complexes generally overlaps with the frequency band of noise. The authors in [6], [16], [17], and [18] employed the Wavelet Transform method for denoising of the ECG signal. In general, this technique decomposes the signal into various components that appear at different scales. It also uses a linear operation, which makes it suitable to preserve the important phase information of the signal. Dinh *et al.* [19] proposed to use the cubic spline wavelet and interpolation for accurate QRS detection. It concludes that wavelet functions that support symmetry and compactness achieve the highest accuracy on the ECG readings in MIT-BIH arrhythmia database.

Pan and Tompkins [1] detected the fiducial points by finding the highest squared slope during high spectral energy of ECG waves. Based on the observations, the above technique is resulted in more number of fiducial points other than the actual QRS complexes. Two adaptive thresholds are considered and the highest among the two thresholds was chosen to extract QRS complex from the ECG signal and the integration of the ECG signal. A search back algorithm was also applied if no QRS complex candidates were found within a certain time interval. They demonstrated a very good performance of 99.325% when tested against the MIT-BIH open-source arrhythmia database [14].The ECG signal parameters are extracted from the QRS complex, the ST segment, and the statistical characteristics of the signal. The selected parameters are divided into two main categories namely morphological and statistical features. Extractions of morphological features were achieved using signal processing techniques and detection of statistical features was performed by employing mathematical methods.

A more robust feature-extraction method [20] is the wavelet transform, which has been successfully employed to extract information for arrhythmia classification. Their features included six energy descriptors derived from the wavelet coefficients over a single-beat interval from the ECG signal and nine different continuous and discrete wavelet transforms were used as attributes of the feature vector. It was found that a Daubechies Cardiology and Heart Disease Diagnosis 183 wavelet transform could provide an overall correct classification of 97.5% with 100% correct classification for both ventricular fibrillation and VT.

In addition to detecting CVD, wavelet transforms can also be used alone to explore ECG waveform and its characteristics. Multiscale features of the wavelet transform have been extracted from the QRS complex and used to successfully distinguish between high P or T waves, noise, baseline drift, and motion artifacts. It was shown that the detection rate for QRS waveforms was above 99.8% for the MIT–BIH database [14] and the P and T waves could be correctly detected, even in the presence of serious baseline drift and noise. Sahambi et al. [18] believed that the timing difference between various intervals of the QRS wave were more important than the subjective assessment of ECG morphology. In these cases, the wavelet transformation was employed to detect the onset and offsets of P and T waves in the QRS complex and the system was developed to continually apply the wavelet transform to ECG waveforms.

C. Different Types of Feature Selection / Dimensional Reduction Methods

It is usual to find that a subset of the feature set would produce better classification rather than using all the features. This is because inclusion of redundant features with poor discriminative power may confuse the classifier, it act as noise and negatively affect the outcome of the classifier. Feature selection is, therefore, of utmost importance in developing a more accurate model for biomedical systems. The following methods are used to select an optimal set of features to represent the problem. High dimension of feature vectors increases computational complexity, and therefore, in order to reduce the dimensionality of the extracted feature vectors (feature selection) statistics over the set of the power levels of the Power Spectral Densities (PSD) [21] were used. The maximum, minimum, mean, and standard deviation of the PSD power levels were estimated by the Pisarenko, MUSIC, and minimum norm methods, respectively. The diverse feature vectors were computed by the usage of the MATLAB software package

Principal Component Analysis (PCA): In large data sets with many features, it may be more efficient to find a smaller and more compact feature representation using a feature transformation. One method is to use PCA [22], which applies a projection to the features to find a reduced representation. The principal component vectors are constructed so that they are orthogonal to one another and hence have maximum variance (principal components). Generally, the training data is first normalized to zero mean and unit variance before application of the PCA algorithm. PCA has been used in many ECG applications, some of which include filtering of ECG beats [7], analysis of features extracted from the QRS complex [13], computer simulations of the cardiovascular system [15], individual beat recognition, and diagnosis of CVD from ECG.

Independent Component Analysis (ICA): ICA [21] is usually applied to blind signal processing. It extracts the independent components (ICs) of the mixed signals. Its foundation is that the signal sources are independent. The sources of standard ECG signal are atrial and ventricular. The signal of atrial-wave is weak, and the signal of ventricular-wave can be divided into de-polarization wave and re-polarization wave. The independence of these waveforms is very well from the physiological sense, so the original ECG signal can be estimated through ICA model. It also proves that selecting relevant features from the over complete feature set could improve the recognition performance.

Genetic and evolutionary methods: This is an unsupervised method that uses an evolutionary approach to prune the feature set. A clustering method is used to determine separability of the features [9] and iteratively retain only the most separable features. It can be used in conjunction with classifiers such as SVM [11] to select the features that minimize generalization errors.

D. Neural Network as a classifier and Optimization methods

In this study, supervised and unsupervised neural networks with appropriate optimization methods are discussed for the classification of ECG signal.

D.1 Multi Layer Perceptron (MLP)

The multilayer perceptron is a supervised (static feed forward) neural network that can have virtually any number of hidden layers besides the essential input and output layers of neurons. Practically one or two hidden layers are enough to model complex systems [23]. Usually the error back propagation [24] method is the preferred learning method to train the network. In such learning the error yielded at the output neuron is propagated back along the layers of the network and the weights are corrected. The output is compared with the desired output of the sample presented at the input. The error $E_i(t)$ for the output neuron i and a given input sample is given as:

$$E_i(w,t) = \left\| d_i(t) - y_i(t) \right\| \tag{1}$$

where d_i is the desired output and y_i is the observed output of neuron i at time instant t of the training process. The observed output y_i of a simple three layer network with one output neuron can be given as:

$$y_i = g\left(\sum_{j=1}^{n} w_{ij} \cdot h_i\left(\sum_{k=1}^{m} w_{jk} z_k + w_{j0}\right) + w_{i0}\right) \tag{2}$$

where g and h are the activation functions of the output and hidden layer neurons respectively. The exponent n and m represents the total number of neurons in the hidden and input layers respectively, and w*'s* are the weights and z_k is the input example.

Using the theory of gradient descent learning, each weight in the network is updated by correcting the present value of the weight with a term proportional to the error at the weight, given as

$$w_{kj}(t+1) = w_{kj}(t) + \eta \delta_j(t) z_k(t) \tag{3}$$

where η is the learning rate parameter whose value is between 0 and 1. δ is the value of local error propagated from the output error $E_i(t)$.

The back propagation is a gradient descent minimization procedure used to minimize the cost functional of the feed forward neural network which is a function of the weights of the network and these weights are changing with time. So, the back propagation learning algorithm tries to find minimum point on the surface formed by the weights of the network.

Since all the error computations are based on the local information of the dataset and network, it is always likely that the learning process may trap in local minima. In order to avoid local minima, a momentum term can be used

$$w_{kj}(t+1) = w_{kj}(t) + \eta \delta_j(t) z_k(t) + \mu \Delta w_{kj}(t) \tag{4}$$

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where μ is the momentum constant which can have values between 0 and 1, Δw is the change in weight in iteration t and t-1.

The search for the parameters η and μ is a trial and error problem. In [26] a method based on the fuzzy inference system is used to change these parameters adaptively as the learning process progress. This method enables the learning process to avoid the local minima as well as results in faster convergence.

D.2 Radial Basis Function (RBF)

The radial basis function network is an unsupervised, three layer feed forward fully connected network, which uses radial basis functions as the only nonlinearity in the hidden layer neurons. The output layer has no nonlinearity. Only the connections of the output layer are weighted whilst the connections from the input to the hidden layer are not weighted [25]. The activation function of the hidden layer can be expressed as:

$$h_i(z_k, m_i, \sigma_i) = \exp\left[-\|z_k - m_i\|^2 / \sigma_i\right] \tag{5}$$

Where z_k , m_i, and σ_i are the input training sample, centre of the i^{th} Gaussian, and width of the i^{th} Gaussian respectively. These functions are called the radial basis functions and the final output is the sum of the connection's weight times these functions.

$$y_j = \sum_{i=1}^{H} w_{ji} h_i \tag{6}$$

The training process is similar to the one for back propagation network, where a cost function like (1) is iteratively minimized. The cost function is a function of the weights in the output layer, the centroids and widths of the radial basis functions. The learning process is not implemented as single procedure, but rather three step procedures are adapted. First the centroids of the radial basis functions are determined using a clustering method like K-means, second the receptive width σ_i are determined using heuristic p-nearest neighbours method and last the weights of the final layer are determined simply by a linear least square regression [27].

D.3 Support Vector Machines (SVM)

Support Vector Machine is an unsupervised or self organized neural network. SVM have recently found considerable attention in classification problems due to its generalization capabilities. These classifiers maximize the distance (margin) between the training examples and the decision boundaries by mapping the training examples to higher dimensional space [28, 29]. The dimension of the new space is considerably larger than that of the original data space. Then the algorithm finds the hyper plane in the new space having the largest margin of separation between the classes of the training data using an optimization technique known as the risk minimization. For a binary classification problem where there are only two classes in the training data = $\{-1,1\}$, a hyper plane can be defined as:

$$W.x + b = 0 \tag{7}$$

where W is the normal to the hyper plane and b / W is the shortest distance of the plane from the origin.

For a good classification model, the positive and negative examples of the training data should fulfill the following two conditions:

$$\begin{aligned} W.x_i + b &\geq +1, \quad \text{for } y_i = +1 \\ W.x_i + b &\leq -1, \quad \text{for } y_i = -1 \end{aligned} \tag{8}$$

These inequalities can be combined into one set of inequalities

$$y\,(W.x + b) \geq 1, \text{ for } \forall\, i \tag{9}$$

The SVM finds an optimal hyper plane responsible for the largest separation of the two classes by solving the following optimization problem subject to the condition in (9)

$$Min_{w,b} \ \tfrac{1}{2} W^T W \tag{10}$$

The quadratic optimization problem of (9) and (10) can be solved using a langrangian function

$$L_p(w,b,\alpha) = \tfrac{1}{2} W^T.W - \sum_{i=1}^{m} \alpha_i (y_i(W.x_i + b) - 1) \tag{11}$$

where α_i are the constants known as langrange multipliers. The solution of (11) for α_i determines the parameters w and b of the optimal hyper plane.

We thus obtain a decision function for the binary classification as:

$$f(x) = \text{sgn}\left(\sum_{i=1}^{m} y_i \alpha_i \langle x, x_i \rangle + b\right) \tag{12}$$

In any classification task only a few langrangian multipliers α_i tend to be greater than zero and the corresponding training vectors are the closest to the optimal hyper plane and are called the support vectors. In nonlinear SVM, the training samples are mapped to a higher dimensional space with the help of a kernel function *K(xi ,xj)* instead of the inner product *<xi , xj>* . Some of the famous kernel functions are the polynomial kernels, radial basis function kernels, and sigmoid kernels [30].

D.4. Particle Swarm Optimization (PSO) Method

Swarm intelligence is a relatively new approach to problem solving that takes inspiration from the social behaviours of insects and of other animals. In particular, the particle swarm optimization method (PSO) is made up of a large number of interacting elements (the particles). Although the nature of the elements and of the interactions is simple, understanding the dynamics of the whole is nontrivial. The particles are provided with memory and the ability to decide when to update the memory. This means that from one iteration to the next, a particle may be attracted towards a new pi or a new pg or both. Thirdly, forces are stochastic [32]. This prevents the use of standard mathematical tools used in the analysis of dynamical systems. Fourthly, the behaviour of the PSO depends crucially on the structure of the fitness function. However, there are infinitely many fitness functions, and so it is extremely difficult to derive useful results that apply to all, even when complete information about the fitness function is available.

PSO is a stochastic optimization technique introduced recently by Kennedy and Eberhart, inspired by the social behaviour of bird flocking and fish schooling [32].

Similar to other evolutionary computation algorithms, such as Genetic Algorithms (GAs) [31], PSO is a population-based search method that exploits the concept of social sharing of information. This means that each individual (called *particle*) of a given population (called *swarm*) can benefit from the previous experiences of all other individuals in the same population. During the iterative search process in the *d*-dimensional solution space, each particle (i.e., candidate solution) will adjust its flying velocity and position according to its own flying experience as well as those of the other companion particles in the swarm.

Let us consider a swarm of size *S*. Each particle *Pi*(*i* = 1, 2, . . . , *S*) in the swarm is characterized by:

1) its current position $\mathbf{p}_i(t) \in \Re^d$, which refers to a candidate solution of the optimization problem at iteration *T*;

2) its velocity $\mathbf{v}_i(t) \in \Re^d$; and

3) the best position $\mathbf{p}_{bi}(t) \in \Re^d$ identified during its past trajectory.

Let $\mathbf{p}_g(t) \in \Re^d$ be the best global position found over all trajectories travelled by the particles of the swarm. Position optimality is measured by means of one or more fitness functions defined in relation to the considered optimization problem.

During the search process, the particles move according to the following equations:

$$\mathbf{v}_i(t+1) = w\mathbf{v}_i(t) + c_1 r_1(t)\left(\mathbf{p}_{bi}(t) - \mathbf{p}_i(t)\right) + c_2 r_2(t)\left(\mathbf{p}_g(t) - \mathbf{p}_i(t)\right) \quad (13)$$

$$\mathbf{p}_i(t+1) = \mathbf{p}_i(t) + \mathbf{v}_i(t) \quad (14)$$

where *r*1 (·) and *r*2 (·) are random variables drawn from a uniform distribution in the range [0,1] so as to provide a stochastic weighting of the different components participating in the particle velocity definition. c_1 and c_2 are two acceleration constants regulating the relative velocities with respect to the best global and local positions, respectively. In greater detail, these parameters are considered as scaling factors that determine the relative pull of the best position of the particle and the global best position.

Sometimes, it is referred to them as the cognitive and social rates, respectively. They are factors determining how much the particle is influenced by the memory of its best location and by the rest of the swarm, respectively. The inertia weight *w* is used as a trade off between the global and local exploration capabilities of the swarm. Large values of this parameter permit better global exploration, while small values lead to a fine search in the solution space. Equation (13) allows the computation of the velocity at iteration *T* + 1 for each particle in the swarm by combining linearly its current velocity (at iteration *T*) and the distances that separate the current particle position from its best previous position and the best global position, respectively. The particle position is updated with (14). Both (13) and (14) are iterated until convergence of the search process is reached.

Typical convergence criteria are based on the iterative behaviour of the best value of the adopted fitness function(s) or/and simply on a user-defined maximum number of iterations. A new particle swarm optimization method (NPSO) is compared with the regular particle swarm optimizer (PSO) invented [32] based on four different benchmark functions. PSO is motivated by the social behaviour of organisms, such as bird flocking and fish schooling. Each particle studies its own previous best solution to the optimization problem, and its group's previous best, and then adjusts its position (solution) accordingly. The optimal value will be found by repeating this process. In the NPSO proposed here, each particle adjusts its position according to its own previous worst solution and its group's previous worst to find the optimal value. The strategy here is to avoid a particle's previous worst solution and its group's previous worst based on similar formulae of the regular PSO. Under all test cases, simulation shows that the NPSO always finds better solutions than PSO.

E. Output Module:

Output module diagnoses the Cardiac abnormalities like ventricular arrhythmias (i.e. Ventricular Late Potential, Ventricular Fibrillation, Ventricular flitter, Ventricular Tachycardia, Polymorphic ventricular tachycardia, Sustained ventricular tachycardia, Non-sustained ventricular tachycardia, Pulse less ventricular tachycardia Dieses).

The performances of the classification [32-34] are expressed in terms of sensitivity (*Sen*), specificity (*Spe*), and positive predictivity (*Ppr*), accuracy (Acc), average accuracy (AvAcc) and overall accuracy (OA). Their respective definitions using true positive (*TP*), true negative (*TN*), false positive (*FP*), and false negative (*FN*), all of which can be obtained from the classification results, are as follows:

- True positive (TP) are beats which have been correctly assigned to a certain class
- True negative(TN) are beats which have been wrongly assigned to a certain class
- False positive (FP) are beats which have been incorrectly assigned to that same class.
- False negative (FN) occurs when a beat should have been assigned to that class but was missed and assigned to another class.
- Sensitivity is the rate of correctly classified events among all events, *Sen =TP/(TP+FN)*;
- Specificity is the rate of correctly classified non events among all non events, *Spe =TN/(TN+FP)*;
- Positive Predictivity is the rate of correctly classified events in all detected events, *Ppr= TP/(TP+FP).*
- Accuracy (Acc) measures the overall system performance over all classes of beats
- Average accuracy (AvAcc) is the average over the Spe and the five values of Sen

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- Overall accuracy (OA) is the percentage of correctly classified beats among all the beats considered (independently of the classes they belong to); are used to quantify the performance of the proposed system with respect to detection of each class of beat.

Accuracy is usually the most crucial metric for determining overall system performance, however due to large variation in the number of beats from different classes in the long-term ECG dataset, sensitivity, specificity, and positive predictivity can too be critical and relevant performance criteria for medical diagnosis.

III DISCUSSION

In this study comparisons of the performance of SVM and two types of neural networks in their ability to classify biologically signal. A number of neural networks strategies have been applied to find the best networks for the feed forward MLP and RBF neural networks, which are then compared with best SVM model obtained.

All the classifiers were used in this study are of multiple target classifications and the number of targets was the three classes, i.e. various types of inhibitors. The dataset have been partitioned into two parts: a training part which is used for training of the algorithm and a test part which is used for testing. The percentage of training and testing portions of the dataset was varied in order to study the variation of performance caused by change in the ratio of training to testing partitions of dataset. The training/testing partitions used to contain (10%, 90%), (30%, 70%), (50%, 50%), (70%, 30%) and (90%, 10%) of the dataset. For the selection of samples in training and testing portions, interleaved method was used to make it sure that percentage of each class in each portion is preserved.

In this review, two types of neural networks, feed forward neural network and a radial basis function neural networks with one hidden layer were considered. The networks were tested for a variable number of hidden layer neurons. The number of input layer neurons was the same as the number of inputs which correspond to the number of variables in the dataset and in the output layer there were three neurons corresponding to the three target outputs. The output can range between (0, 1). The training samples were presented to the neural networks, the output was compared with the desired output for a given input sample and the errors were back propagated for the update of weight vectors.

Table.2 Performance Analysis of Various ECG Classification Model

Classifier Model	**Characteristics**	**Classifier Performance**	**Remarks**
SVM based PSO classifier [23]	Applicable to morphology, temporal features and also for wavelets and high-order statistics	91.67% High	Classifier with other Optimization Criterion is used individually or jointly depending on the application requirements.
WT based RBF [37]	Well suited to classifying the arrhythmia, owing to the feature vectors' linear inseparability and tendency to cluster.	97.5% High	Obtaining additional data to enhance the RBFNN classifier and thereby improve the feature set formulation
Higher order statistics (HOS) SVM [36]	Two different pre processing processes integrated into one expert system to improve the overall accuracy of heartbeat recognition. The classifiers have been combined using weighted voting principle.	94% High	Highly reliable classifier can be obtained by combining a number of classifiers, which exhibit an average performance.
Modified mixture of experts (MME) [28]	MME trained on the diverse features accuracy rates higher than that of the other automated diagnostic systems. CPU time (min : sec) 4.51. Classification of the ECG beats is done based on misclassification rates. It enhances the diagnostic capabilities of physicians and reduce the time required for accurate diagnosis.	99.4% High	Further increase of the accuracies could be achieved by feeding the classifier with other kinds of features (e.g., those based on wavelets or high order statistics) together with or in substitution to the morphological ones.
Classifier Model	**Characteristics**	**Classifier Performance**	**Remarks**

Multilayer perceptron neural network (MLPNN) [23]	CPU time(min : sec) 7:31	97.78% High	
Combined neural network(CNN) [21]	CPU time(min : sec) 9:15	96.67% High	
Mixture of experts (ME) [8]	CPU time(min : sec) 10:24	95% High	
Iterative procedure - SVM Classifier [24]	1) Margin sampling (MS) in which the samples of the learning set more close to the hyper planes between the different classes are chosen; 2) Posterior probability sampling (PPS) in which posterior probabilities are estimated for each class. Then, the samples that maximize the entropy between the posterior probabilities are selected 3) Query by committee (QBC) in which a pool of classifiers is trained on different features to label the set of learning samples.	79.07% Low 79% Low 79% Low	More sophisticated training set initialization strategy could further improve the performance
Independent Component analysis (ICA) and back propagation NN [26]	1) Mixture of experts (MOE) - only 23 independent components. 2)Fourier-Transform neural network (FTNN) 3)Fuzzy hybrid neural network (Fhyb-HOSA) 4)BSS (BSS-Fourier) 5)Multi-resolution analysis and neural network (DWT-NN)	98.37 % High 94.0 % Medium 98.0 % High 96.06% High 96.79 %High	Further increase the number of ICs does not increase the classification accuracy, with appropriate Feature reduction technique performance is improved

The networks have been trained and tested with variable ratio of samples from the dataset. The behaviour of both the network is almost similar. As the training data is increased the accuracy of prediction increases, but it is not good when the number of training examples is very large than the testing examples. The MLP network gives the best prediction accuracy when the training/ testing ratio is 50%, whereas the RBF network prediction is best when it is trained with 10% and tested with 90% of examples in the dataset.

IV. CONCLUSION

This paper exposed a comparative table evaluating the performance of different algorithms that were proposed earlier for ECG signal QRS Detection is shown in Table.2 and Gray area of these classifiers are also given. The PSO-based approach [23] which aim at optimizing the performances of SVM classifiers in terms of classification accuracy by detecting the best subset of available features and solving the tricky model selection issue. In this feature selection is done in fully automatic way, which makes it particularly useful and attractive. The results confirm that, the PSO–SVM classification system substantially boosts the generalization capability achievable with the SVM classifier, and its robustness against the problem of limited training beat availability, which may characterize pathologies of rare occurrence. Improving the accuracy of diagnosing the CVD at the earliest is necessary in the case of patient monitoring system. Therefore our future work will augment the diagnosing accuracy of the CVD. All these methodologies will provide the information to the reader about the best and optimum ECG signal pre-processor, feature generator, feature selector and Optimized classifier techniques for QRS Detection.

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