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Classification of ECG Signals Using Particle Swarm Optimization and Extreme Learning Machine

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Abstract

The ECG is one of the mainly effective investigative tools to detect cardiac diseases. It is a technique to calculate and record dissimilar electrical potentials of the heart. The electrical potential generated by electrical action in cardiac tissue is calculated on the surface of the human body. Present flow, in the variety of ions, signals reduction of cardiac muscle fibers important to the heart's pumping action. This ECG can be classified as standard and abnormal signals. In this work, a systematic experimental study was conducted to demonstrate the advantage of the generalization capability of the Particle Swarm Optimization Extreme Learning Machine (PSO-ELM) compared with Extreme Learning Machine (ELM) approach in the automatic classification of ECG beats. The simplificationpresentation of the ELM classifier has not attained the nearest maximum accuracy of ECG signal classification. To attain the maximum accuracy the PSO-ELM classifier design by searching for the best value of the parameters that tune it'sdistinguish function, and upstream by looking for the best subset of features that feed the classifier. The experiments were conducted on the ECG data from the Massachusetts Institute of Technology–Beth Israel Hospital (MIT– BIH) arrhythmia database to categorize five kinds of abnormal waveforms and normal beats. In particular, the sensitivity of the PSO-ELM classifier is tested and that is compared with ELM. The attained results clearly confirm the superiority of the PSO-ELM approach when compared to ELM classifiers.

Keywords: Electrocardiogram (ECG) signals classification, Extreme Learning Machine (ELM), Particle Swarm Optimization ELM (PSO-ELM).

Introduction

The detection of the ECG beats is an enormously important task in the coronary intensive unit, where the classification of the ECG beats is necessary tool for the diagnosis. ECG is a method which captures transthoracic explanation of the electrical activity of the heart over time and externally recorded by skin electrodes. It is a non determined recording created by an electrocardiographic machine. ECG offers cardiologists with functional information about the rhythm and functioning of the heart. Therefore, its investigation representsacapable way to detect and treat different kinds of cardiac diseases. The ECG signal is typically divided into two phases: depolarization and repolarization phases. The depolarization phase corresponds to the P-wave and QRS-wave while repolarization phase corresponds to the T-wave and U-wave.

The ECG is calculated by placing ten electrodes on favored spots on the human body surface. For regular ECG recording, the deviations in electrical potentials in 12 dissimilarinformation out of the ten electrodes are calculated. These 12 dissimilar electrical explanations of the activity in the heart are usually referred to as leads. Trained physicians are able to distinguish certain model in a patient's ECG signal and use them as the origin for diagnosis. Researchers have tried as the beginning of computers to enlarge techniques and algorithms for mechanical processing of ECG signals for a variety of medical applications.

The many algorithms have been introduced for the appreciation and classification of ECG signal. Some of them use time and some use regularity domain for description. Based on that numerous specific attributes are defined, allowing the appreciation between the beats belonging to dissimilar pathological classes. The ECG waveforms may be different for the similar patient to such extent

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that they are unlike each other and at the same time alike for dissimilar types of beats.

The aim of this work is twofold. First, they present a thorough experimental study to demonstrate the advantage of the simplification capability of the Extreme Machine Learning (ELM) approach in the mechanical classification of electrocardiogram (ECG) beats. Second, theysuggest a novel categorization system based on Particle Swarm Optimization to get better the simplification performance of the ELM classifier. For this reason, they have optimized the ELM classifier design by searching for the best value of the parameters that tune its discriminate function, and upstream by looking for the best subset of features that feed the classifier. The obtained results clearly confirm with the ELM approach, and suggest that additionalconsiderable improvements in terms of classification accuracy can be obtained by the proposed PSO-ELM classification system. The PSO-ELM yielded ahigher accuracy than ELM.

Literature survey

Jadhav*et al* (2010) proposed amechanical Artificial Neural Network (ANN) based classification scheme for cardiac arrhythmia using standard 12 lead ECG recordings. In this learning, they are largely interested in producing high confident arrhythmia classification results to be appropriate in analytical decision support systems. In arrhythmia analysis, it is inescapable that a number of attribute values of a person would be absent. Therefore they have replaced these missing attributes by closest column value of the concern class.

Traditional Extreme Learning Machine (ELM) may need high amount of hidden neurons and lead to ill-condition trouble due to the random determination of the input weights and hidden biases. In this work, they use a modified Particle Swarm Optimization (PSO) algorithm to select the input weights and hidden biases of Single-hidden-Layer Feedforward Neural Networks (SLFN) and Moore–Penrose (MP) universal inverse to systematicallydecide the output weights are measured by Han *et al* (2012).

The commonreason optimization technique known as Particle Swarm Optimization has received much concentration in past years, with a lot of attempts to discover the alternate that carry out best on a wide range of optimization problems. The focus of past research has been with manufacture the PSO method additional complex, as this is frequently believed to enlarge its flexibility to other optimization problems. This study takes the opposite approach and simplifies the PSO method is shown by Pedersen and Chipperfield (2010).

Sharma *et al* (2010) propose a novel denoising technique based on valuation of higher-order statistics at dissimilar Wavelet bands for an electrocardiogram (ECG) signal. Higher-order statistics at dissimilar Wavelet bands provides significant information regarding the statistical nature of the information in time and frequency. The fourth order cumulant, *Kurtosis*, and the Energy Contribution Efficiency (ECE) of signal in a Wavelet subband are joint to assess the noise content in the signal.

The categorization of the ECG signals is currentlyexecuted with the extreme learning machine. The simplification presentation of the SVM classifier is not enough for the correct arrangement of ECG signals. To overcome this problem, the SVM classifier is used which works by searching for the best value of the parameters that tune it'sdistinguish function and upstream by looking for the most excellent subset of features that feed the classifier. In this work, a methodical experimental study was completed to show the advantage of the generalization capability of the Extreme Learning Machine (ELM) that is obtainable and compared with support vector machine (SVM) advance in the automatic categorization of ECG beats sre developed by Karpagachelvi *et al* (2012).

Dutta *et al* (2010) proposes the development of amechanical medical analytical tool that can categorize ECG beats. This is measured a significant problem as accurate, timely detection of cardiac arrhythmia can help to offer proper medical attention to cure/decrease the ailment. The proposed method makes use of a cross-correlation based approach where the cross-spectral density information in regularity domain is used to take out suitable features. A least square support vector machine (LS-SVM) classifier is constructed utilizing the features so that the ECG beats are confidential into three categories: normal beats, PVC beats and other beats.

Ye *et al* (2012) proposed a original approach for heartbeat classification based on a grouping of morphological and dynamic features. Wavelet transform and Independent Component Analysis (ICA) are applied discretely to each heartbeat to extract morphological features. In addition, RR interval information is computed to offerenergetic features. The proposed method is validating on the baseline MIT-BIH arrhythmia database and it yields anmost excellent accuracy.

Korürek and Dogan (2010) presents a technique for electrocardiogram (ECG) beat

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classification based on Particle Swarm Optimization and Radial Basis Function Neural Network (RBFNN). For categorization stage of the extracted features, a RBFNN structure which is evolved by element swarm optimization is used. A number of experiments are carrying out over the test set and it is observed that the proposed method classifies ECG beats with a lesser size of system without creation any concession on the classification presentation.

The ECG categorization problems have been resolved by means of a methodology, which has the potential to improve the ECG classification performance. This technique diminishes the computational difficulty which mostly occurs during the feature selection. The proposed system utilizes particle swarm optimization for the selection of feature subset. PSO is good-looking for feature selection, in that particle swarms will discover best feature grouping as they fly within the best subset space. Thus ELM is used for classification, which is based on local estimate strategy. It diminishes the amount of operations in learning mode and it is well suitable for better datasets given by Muthulakshmi and Latha (2012).

Lan*et al* (2010) effort to address the architectural plan of ELM revert or by applying a productivetechnique on the basis of ELM algorithm. After the nonlinearities of ELM system are fixed by randomly produce the parameters, the network will communicate to a linear regression model. The collection of hidden nodes can then be observed as a subset model selection in linear regression. The plannedproductive hidden nodes selection for ELM (referred to as CS-ELM) selects the bestamount of hidden nodes when the unbiased risk judgment based criterion *CP* reaches the minimum value.

Extreme learning machine (ELM) was proposed as a fresh class of learning algorithm for single-hidden layer feedforward neural network (SLFN). To attainexcellent generalization presentation, ELM reduce training mistake on the complete training dataset; therefore it might suffer from overfitting as the learning model will estimated all training samples well is given by Liu and Wang (2010).

Figueiredo and Ludermir (2012) perform the Extreme Learning Machine (ELM), that has been hybridized with the Particle Swarm Optimization (PSO). This hybridization is named PSO-ELM. In the majority of these hybridizations, the PSO uses the global topology. The presentation of PSO depends on its topology, and there is not a greatest topology for all problems. Thus, in this work, they examine the produce of the PSO topology on performance of the PSO-ELM.

Extreme Learning Machine was a new type of feed forward neural network. Contrast with traditional single hidden layer feed forward neural networks, ELM possessed higher training speed and smaller error. A new ELM learning algorithm, which was optimized by the Particle Swarm Optimization, was planned. PSO algorithm was utilized to choose the input weights and bias of hidden layer, and then the output weights could be designed by Wang and Bi (2013).

Recently Extreme Learning Machine (ELM) for Single-Hidden-Layer Feedforward Neural Networks has been attracting attentions for its quicker learning speed and improved generalization performance than those of traditional gradient-based learning algorithms. In this work, a hybrid learning algorithm is planned to overcome the drawbacks of ELM, which uses an enhanced PSO algorithm. In order to achieve optimal SLFN, the enhanced PSO optimizes the input weights and hidden biases are done by Li and Niu (2013).

Methodology

Feature extraction

Mechanical ECG beat appreciation and categorization is carry out in the part either by the neural network or by the other detection systems relying in various features, time fieldillustration, extracted from the ECG beat or the measure of energy in a band of frequencies in the spectrum (frequency domain representation). Since these features are very at danger to variations of ECG morphology and the temporal characteristics of ECG, it is tricky to differentiate one from the other on the basis of the time waveform or frequency demonstration. In these work three different classes of characteristic set are used belonging to the isolated ECG beats including; third-ordercumulant, auto-regressive model parameters and the variance of discrete wavelet transform detail coefficients for the different scales.

Wavelet transformation

Physiological signals used for judgment are normally characterized by a non-stationary time performance. For such patterns, time and frequency representation are attractive. The frequency characteristics in calculation to the temporal performance can be explained with respect to uncertainty principle. The wavelet transform can characterize signals in dissimilar resolutions by dilating and compress its basis function. While the enlarge functions adapt to slow wave action, the

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compressed functions captures quick activity and sharp spikes. The most favorable option of types of wavelet function for pre-processing is difficulty dependent. In this work Daubechies wavelet function (db5) which is called efficiently support orthonormal wavelets. By manufacture discretization the scaling feature and location factor the DWT is achieved. For orthonormal wavelet transform, x(n) the separate signal can be extended in to the scaling function at j level, as follows:

$$x(n) = D_{j,k}[x(n)] + A_{j,k}[x(n)], n \in Z \qquad (1)$$

Where $D_{j,k}$ correspond to the detailed signal at j level. Note that j controls the dilation or reduction of the scale function Φ(t) and k indicate the location of the wavelet function Ψ(t), and n characterize the sample amount of the x(n). Here n∈Z represents the set of integers. The regularity spectrum of the signal is classified into elevatedregularity and shortregularity for wavelet decomposition as the band enlarge (j = 1, . . . , 6).Wavelet convert is a two-dimensional time scale processing technique for non-stationary signal with sufficient scale standards and shifting in time.

Multiresolution decomposition can powerfullyofferinstantaneous characteristics, in phrase of the demonstration of the signal at numerous resolutions subsequent to dissimilar time scales. Feature vectors are building by the normalized variances of feature coefficients of the DWT which belong to the associated scales.

Higher-order statistics and AR modeling

The major difficulty in mechanical ECG beat detection and categorization is that connected features are very vulnerable to variation of ECG morphology and sequential characteristics of ECG. In the study the set of innovative QRS difficultdistinctive for six types of arrhytmia taken from the MIT/BIH arrhytmia database, there is a hugedifference of signal between the similartypes of beats belonging to the same type of arrhytmia. Therefore, in order to work out such problem, the author will rely on the numerical features of the ECG beats. In this work for this aim, third-order cumulant has been taken into description, which can be determinedas follows:

$$C_{2x}(k) = E\{x(n)x(n+k)\} \qquad (2)$$

$$C_{3x}(k,l) = E\{x(n)x(n+k)x(n+l)\} \qquad (3)$$

$$C_{4x}(k,l,m) = E\{x(n)x(n+k)x(n+l)x(n+m)\} - C_{2x}(k)C_{2x}(m-l) - C_{2x}(l)C_{2x}(m-k) - C_{2x}(m)C_{2x}(l-k) \qquad (4)$$

Where E represents the anticipation operator, and k, l andm are the time lags. In this work,third-order cumulate of chosen ECG beats is utilized. Normalizedten points represents the cumulant consistentlydistributed with in the series of 25 lags.Everyfollowing samplesof a signal as a linear grouping of precedingsamples, that is, as the output of an all-pole IIR filter is modeled by linear calculation.This procedure locates the coefficients of an n^{th}orderauto-regressive linear procedure that modelsthe time series x as

$$x(k) = -a(2)x(k-1) - a(3)x(k-2) - \cdots - a(n+1)x(k-n-1) \qquad (5)$$

where x represents the real input time series (a vector), andn is the order of the denominator polynomial a(z).In the block processing, autocorrelation technique is one of the modeling methods of all-polemodeling to discover the linear calculation coefficients.This technique is as well called as the Maximum Entropy Method (MEM) of spectral analysis.

Extreme Learning Machine

A new learning algorithm called the Extreme Learning Machine for Single-hidden Layer Feed forward neural Networks (SLFNs) organized batch learning. The production of an SLFN with ~N hidden nodes (additive or RBF nodes) can be represented by

$$f_{\tilde{N}}(X) = \sum_{i=1}^{\tilde{N}} \beta_i G(a_i, b_i, X), \quad X \in R^n, \quad a_i \in R^n, \qquad (6)$$

Wherea_i and b_i are the learning parameters of hidden nodes and β_i is the weight linking the i^{th} hidden node to the output node. $G(a_i,b_i,X)$ is the output of the i^{th} hidden node with respect to the input x. For the preservative hidden node with the establishment function g(x):R→R (e.g., sigmoid or threshold), $G(a_i,b_i,X)$ is given by

$$G(ai, bi, X) = g(a_i . X + b_i), b_i \in R \qquad (7)$$

Where airepresents the weight vector linking the input layer to the i^{th} hidden node and b_i is the bias of the i^{th} hidden node. a_i.xindicate the inner product of vectors a_i and x in R^n. For an RBF hidden

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node with an establishment function g(x):R→R(e.g., Gaussian), G(a_i,b_i,X) is given by

$$G(ai, bi, X) = g(b_i||x - a_i||), b_i \in R^+ \qquad (8)$$

Where a_i and b_i are the i^{th} RBF node'scenter and impact factor. R^+point out the set of all constructive real values. The RBF network is a particular case of the SLFN with RBF nodes in its hidden layer. Each RBF node has its own centroid and contact factor and output of it is given by a radially symmetric purpose of the spaceamong the input and the center.

In the learning algorithms it utilizes a restrictedamount of input-output samples for training. Here, N arbitrary separate samples are measured(x_i,t_i)∈R^nx R^m, where x_i is an n x 1 input vector and t_i is an m x 1 aim vector. If an SLFN with $\tilde{N}$ hidden nodes can estimated N samples with zero error, it then implies that there exist β_i, a_i, and b_i such that

$$F_{\tilde{N}}(X_J) = \sum_{I=1}^{\tilde{N}} B_I G(A_I, B_J, X_J) = T_J, J = 1, \ldots, N \qquad (9)$$

Equation () can be written efficiently as

$$H\beta = T \qquad (10)$$

Where

$$H(a_1, \ldots, a_{\tilde{N}}, b_1, \ldots, b_{\tilde{N}}, X_1, \ldots, X_{\tilde{N}}) = \begin{bmatrix} G(a_1, b_1, X_1) & \cdots & G(a_{\tilde{N}}, b_{\tilde{N}}, X_1) \\ \vdots & \ddots & \vdots \\ G(a_1, b_1, X_N) & \cdots & G(a_{\tilde{N}}, b_{\tilde{N}}, X_N) \end{bmatrix}_{N\times\tilde{N}} \qquad (11)$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\tilde{N}}^T \end{bmatrix}_{\tilde{N}\times m} \text{ and } T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}_{N\times m} \qquad (12)$$

H is called the hidden layer output matrix of the system; the i^{th} column of H is the i^{th} hidden node's output vector with respect to inputs x_1, x_2,…,x_N and the j^{th} row of H is the output vector of the hidden layer with respect to input x_j.

In actualapplication, the amount of hidden nodes, $\tilde{N}$, will forever be fewer than the amount of training samples, N, and, hence, the preparation error cannot be completed exactly zero but can approach a nonzero training error. The hidden node parameters a_i and b_i (input weights and biases or centers and impact factors) of SLFNs need not be tuned during preparation and may just be assigned with random values according to any permanent sampling sharing. Equation (12) then becomes a linear system and the output weights are predictable as

$$\tilde{\beta} = H \dagger T \qquad (13)$$

Where H †the Moore-Penrose is comprehensive inverse of the hidden layer output matrix H. The ELM algorithm which consists of only three steps, can then be summarized as follows

ELM Classification with PSO

The method describing the ELM classificationsystem for the basic discrimination case among two classes isas follows.

1) *Initialization*

Step 1) Generate randomly afirst swarm of size *S*.

Step 2) Set to zero the speed vectors v_i(i=1, 2, . . . , *S*) connected with the *S* particles.

Step 3) For each position $\mathbf{p}_i \in \Re^{d+2}$ of the particleP_i(i= 1, 2, . . . , *S*) from the swarm,train anELM classifier and calculate the matchingfitness function $f(i)$ (i.e., the SV measure).

Step 4) Set the best location of every particle with its initialposition, i.e.,

$$\boldsymbol{P}_{bi} = \boldsymbol{P}_i, (i = 1,2, \ldots, S)$$

2) *Search process*

Step 5) Identify the greatest global position $\mathbf{p}g$ in the swarmexhibiting the smallest value of the measuredfitness function over all explored trajectories.

Step 6) Update the speed of each particle using (14).

$$V_i(t+1) = wv_i(t) + c_1 r_1(t)(\boldsymbol{P}_{bi}(t) - \boldsymbol{P}_i(t)) + c_2 r_2(t)(\boldsymbol{P}_g(t) - \boldsymbol{P}_i(t)) \qquad (14)$$

Step 7) Update the position of each particle using (15).

$$\boldsymbol{P}_i(t+1) = \boldsymbol{P}_i(t) + \boldsymbol{V}_i(t) \qquad (15)$$

If aparticle goes away from the predefined boundaries ofthe search space, abbreviate the updating by settingthe location of the particle at the space boundaryand reverse its searchdirection (i.e.,

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multiply itsspeed vector by –1). This will stop the particlefrom additional attempting to go out of the permittedsearch space.

Step 8) For each candidate particle $\mathbf{p}_i$ (i= 1, 2, . . . ,S),train an ELM classifier and estimate the correspondingfitness function $f(i)$.

Step 9) Update the best position $\boldsymbol{P}_{bi}$of each particle if itspresent position $\mathbf{p}_i$(i= 1, 2, . . . , S) has a lesserfitness function.

3) *Convergence*

Step 10) If the highestamount of iterations is not yetreached, return to step 5.

4) *Classification*

Step 11) Choose the greatest global position $\boldsymbol{P}_g^*$in the swarmand train an ELM classifier fed with the subsetof detected features mapped by $\boldsymbol{P}_g^*$and modeledwith the values of the two parameters C and γencoded in the same position.

Step 12) Categorize the ECG signals with the trained ELMclassifier.

Experimental results

Dataset Description

The experiment conducted on the basis of ECG data from the Physionet database. In exacting, themeasured beats refer to the subsequent classes: Normal sinus rhythm (N), Atrial Premature Beat (A), Ventricular Premature Beat (V), Right Bundle branch block (RB), Left Bundle branchblock (LB), and Paced Beat (/). The beats were chosen fromthe recording of 20 patients, which match to the followingfiles: 100, 102, 104, 105, 106, 107, 118, 119, 200, 201, 202,203, 205, 208, 209, 212, 213, 214, 215, and 217. In order toprovide for the classification procedure, in this work, the twofollowing kinds of features are adopted: 1) ECG morphology features and2) three ECG temporal features, i.e., the QRS complex period,the RR interval (the time span between two consecutive R pointsrepresenting the distance between the QRS peaks of the presentand preceding beats), and the RR interval averaged over the ten last beats. In organize to take out these features, first the QRS finding is performed and ECG wave boundary detectiontasks by means of the well-known ecgpuwave software obtainable. Then, following extracting the three temporal features of interest, normalized to the similar periodic length the period of the segmentedECG cycles according to the process reported.To this reason, the mean beat period was chosen as the standardizeperiodic length, which was represented by 300 uniformlydistributed samples. Accordingly, the total number of morphologyand sequential features equals 303 for each beat.

Table1: Numbers of Training and Test Beats Used In the Experiments

Class		**N**	**A**	**V**	**RB**	**/**	**LB**	**Total**
Training beats		150	100	100	50	50	50	500
Test beats		24000	245	3789	3893	6689	1800	40416

In order to achievedependable assessments of the classificationcorrectness of the investigated classifiers, in all the following experiments,three dissimilar trials are performed, each with a newset of arbitrarily selected training beats, while the test set waskept unmovable. The results of these three trials achieved on thetest set were thus averaged. The detailed amount of trainingand test beats are reported for each class in Table 1. Classificationpresentation was evaluated in terms of four measures,which are: 1) the Overall Accuracy (OA), which is the proportionof properly classified beats among all the beats considered; 2) the correctnessof every class that is the percentage of properly classified beatsamong the beats of the considered class; 3) the Average Accuracy(AA), which is the average over the classification accuracies obtainedfor the dissimilar classes; 4) the McNemar's test that gives the statistical consequence of differenceamong the accuraciesachieved by the different classification advance. This test is based on the standardized normal test statistic

$$Z_{ij} = \frac{f_{ij} - f_{ji}}{\sqrt{f_{ij} - f_{ji}}} \qquad (20)$$

Where Z_{ij} calculates the pair wise statistical implication of the difference among the accuracies of the i^{th} and j^{th}classifiers. f_{ij} stands for the amount of beats classified correctlyand wrongly by the i_{th} and j_{th} classifiers, correspondingly. Accordingly, f_{ij} and f_{ji} are the counts of classified beats on which the considered i_{th} and j_{th} classifiers disagree. At the normallyused 5% level of implication, the dissimilarity of accuracies between the i_{th} and j_{th} classifiers is said statistically significant if $|Z_{ij}| > 1.96$.

Experimental Scheme

The planned experimental framework was performed around the following two main experiments.The first research aimed at assessing the

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efficiencyof the ELM approach in classifying ECG signals openlyin the whole original hyper dimensional characteristic space. The wholeamountof training beatswas fixed to 500, as reported in Table 1. The second experiment was dedicated to examine the simplificationcapability of the ELMclassifiers with and without feature decrease, and of the PSO-ELM classification system by decreasing/increasingthe amount of obtainable training beats. Finally, in the secondtesting, the sensitivityof the PSO-ELM classification system is examined.

4.3 Experimental settings

The correctness of the planned method of PSO-ELM may have high accuracy when evaluate with the ELM. The proposed PSO-ELM has high value in all the methods.

Table2: Overall (OA), Average (AA), and Class Percentage Accuracies Achieved on the Test Beats with the Different Investigated Classifiers with a Total Number of 500 Training Beats

Methods	**OA**	**AA**	**N**	**A**	**V**	**RB**	**/**	**LB**
ELM	**90.54**	**82.61**	**85.97**	**65.25**	**78.11**	**95.26**	**75.83**	**95.22**
PSO-ELM	**95.53**	**94.44**	**93.67**	**95.65**	**89.67**	**97.64**	**93.11**	**96.89**

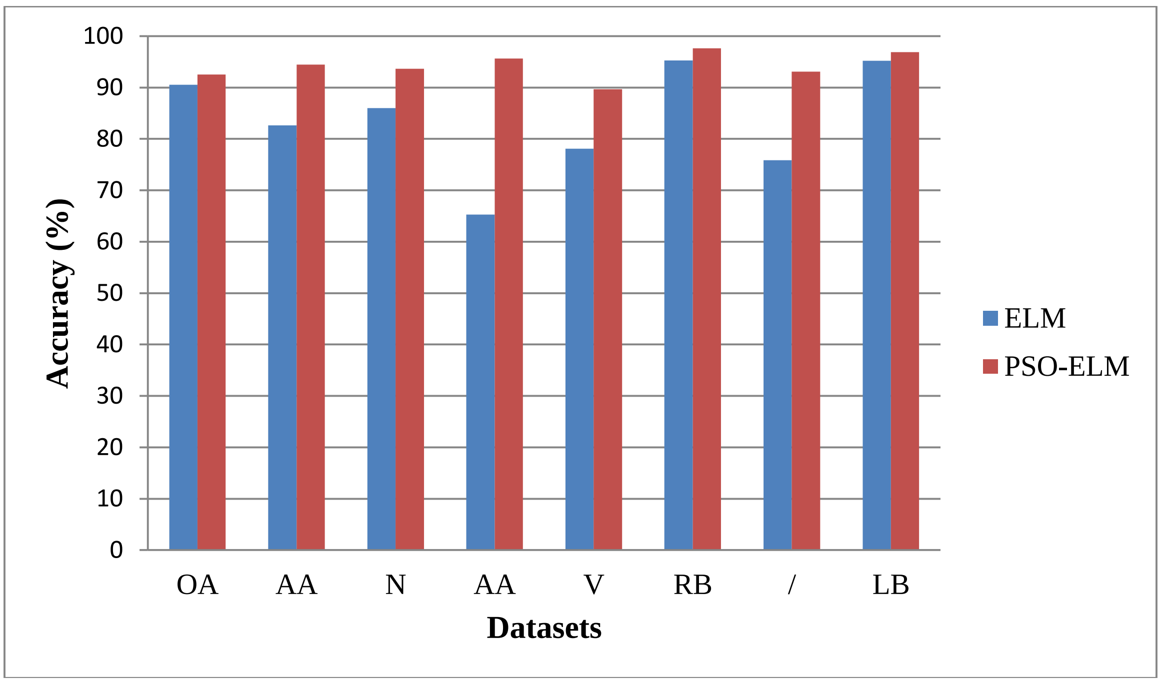

Figure1: Comparison of ELM and PSO-ELM accuracy for different datasets

The Figure 1 gives the accuracy of classifying the ECG signals by using ELM and PSO-ELM. This shows that PSO-ELM gives much improved accuracy for all datasets given as input. In which RB dataset achieves the maximum accuracy of 97.64%.

Table3: Number of Features Detected For Each Class with the ELM Classification System Trained On 500 Beats

Class	**N**	**A**	**V**	**RB**	**/**	**LB**	**AVERAGE**
#Detected Features	68	49	32	50	47	41	47

Table 3 shows the amount of features detected mechanically to distinguishevery class from the others. The average number of featuresrequired by the PSO-ELM classifier is 47, while the minimum and maximum numbers of features were obtained for the ventricularpremature (V) and normal (N) classes with 32 and 68 features, respectively.

Conclusion

In this study, a novel ECG beat classification scheme using PSO-ELM is proposed. The wavelet transforms variance and AR model parameters have been used for the features selection. From the obtained experimental results, it can be strongly recommended that the use of the PSO-ELM approach for classifying ECG signals on account of their superior generalization capability as compared to traditional classification techniques. PSO-ELM approach is proposed for an automatic ECG beat classification. This approach presents methods for improving ELM performance in two aspects: feature selection and parameter optimization. The new method that proposed in this work is the grouping of a Extreme Learning Machine and Particle Swarm Optimization (PSO-ELM). This modified PSO is jointly applied to optimize the feature selection and the ELM kernel parameter.

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