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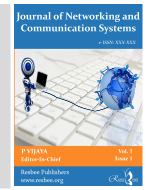

Arrhythmia Classification Using Cat Swarm Optimization Based Support Vector Neural Network

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Abstract: Among various heart diseases in the world, cardiac arrhythmia is one of the deadliest diseases, affecting millions of people. Several automated approaches are exploited for the detection and classification of arrhythmia using ECG signals. Machine learning is a promising approach used intensively in recent years for the arrhythmia classification. Accordingly, in this paper, a technique is proposed for the arrhythmia classification with the introduction of a novel classifier. From the ECG signals, wave components and statistical features are extracted and the constructed feature matrix is subjected to the classification. The arrhythmia classification is performed by the proposed Cat Swarm Optimization-based Support Vector Neural network (CS-SVNN), which is the modification of the SVNN with the optimized training. Thus, the SVNN classifier with the optimally tuned weights and biases classifies the person as either arrhythmia patient or normal. The performance of the proposed technique is determined by three measures, namely accuracy, sensitivity, and specificity, and is compared with the performance attained using the existing methods. The maximum accuracy attained by the proposed CS-SVNN is 98.4%, and this proves the effectiveness of the technique in classifying the arrhythmia patients.

Keywords: Arrhythmia classification, Automated techniques, Machine learning, Cat Swarm Optimization, Support vector neural network, wave components.

Nomenclature

Abbreviations	Descriptions
CS-SVNN	Cat Swarm Optimization-based Support Vector Neural network
ECG	Electrocardiography
CVD	Cardiovascular Disease
KNN	K Nearest Neighbor
SVM	Support Vector Machine
NN	Neural Network
CSO	Cat Swarm Optimization
PSO	Particle Swarm Optimization
GB	Genetic Bat Algorithm
ANN	Artificial Neural Network
PCA	Principal Component Analysis
OPF	Optimum-Path Forest

1. Introduction

In recent years, diseases related to cardiac are growing significantly and moreover, heart disease is one of the deadliest diseases among various sicknesses that humans face [1]. One such important CVD is cardiac arrhythmia, which is a disorder affecting the normal functionality of the heart [2]. In the extreme case of arrhythmias, the ability of the heart in pumping blood might be reduced and leads to breathing shortness, chest pain, failure of consciousness, and tiredness. If a cardiac arrhythmia is left untreated, in a serious condition, it can cause a heart attack or even death. Thus, earlier diagnosis and genuine and advanced treatment of heart-related problems can avoid sudden death of patients to a great extent [1]. ECG signal has a valuable role in diagnosing CVD and revealing all cardiac diseases based on the heartbeat, as the ECG signal shows all the electrical activities of the heart [3]. Nowadays, with the advancements in computer sciences for signal interpretation, ECG analysis has become the most hopeful approach for cardiac diagnostic, providing detailed and valuable information concerning the condition of

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the heart [4]. Therefore, to control any dreadful happenings, always it is better to classify and recognize the cardiac arrhythmia. Various techniques are developed so far for detecting cardiovascular arrhythmias using the ECG signal information [1]. Recently, several automated schemes are introduced for the detection and classification of cardiac arrhythmias in ECG signals so as to diagnose cardiovascular diseases [5].

Generally, the techniques adopted in the state of the art are mostly on the basis of the time domain, frequency domain, and time–frequency-based [3]. The major steps included in the analysis of ECG are the detection of abnormalities, classification, and prediction. The approaches employed for the detection of abnormalities are on the basis of the adaptive sampling [6]. For the ECG feature extraction, several adaptive techniques, like wavelet transform [7] or empirical mode decomposition [4], are used. Usually, to classify the ECG signals, two steps, such as feature extraction and feature selection, are utilized in common. While the feature extraction step extracts the necessary features from the represented patterns for further processing, the significant features are chosen so as to minimize the feature dimension in the feature selection phase. It is noteworthy that any promising method [22] [23] [24] [25] must be employed for the feature selection so that all the important information is preserved [10]. The classification of arrhythmia is carried out using different machine learning techniques, as they have proven its importance in prediction and classification. The classifiers that are used commonly in the recent works for the arrhythmia classification are KNN [8], SVM, and NN [9] [4].

The intention of this paper is to develop a technique for arrhythmia classification by proposing an optimized machine learning method. For the diagnosis of arrhythmia, wave interval features and Gabor features are extracted initially from the ECG signal. The classifier proposed is named CS-SVNN, which is newly designed by modifying the training procedure of SVNN using CSO. With the integration of CSO algorithm in SVNN, weights and biases of SVNN are optimally tuned, as CSO algorithm is advantageous over other heuristic algorithms, like PSO in selecting the global optimal position. Based on the wave features and texture features extracted, the proposed classifier determines the arrhythmia patients.

The paper is organized as follows: Section 2 describes the survey of related works prevailing in the literature along with the challenges, the proposed technique of arrhythmia classification using CS-SVNN is elaborated in section 3, and section 4 demonstrates the results attained by the proposed technique and section 5 states the conclusion of the paper.

2. Literature Review

In this section, few existing works are developed for the arrhythmia classification as follows:

Bhagyalakshmi V *et al.* [10] developed an approach, called GB optimization algorithm for training the SVNN (GB-SVNN), for the classification of arrhythmia using ECG signals. The features extracted using multi-resolution wavelet and the Gabor filters were utilized for extracting the features that were fed to the GB-SVNN, for the arrhythmia classification. Another classification technique was presented by Abdalla, F.Y. *et al.* [3] using non-linearity and non-stationary decomposition approaches. Using different parameters extracted from the feature vector, ANN classified the heartbeats. Even though the utilization of PCA in the dimension reduction could improve the performance, it increases the computational complexity. de Albuquerque, V.H.C *et al.* [5] had utilized supervised machine learning approaches for the automatic detection of arrhythmia in ECG signals with the introduction of a classifier, name OPF. However, the classification accuracy attained by the method requires further improvement, for which the ensemble of classifiers is recommended. Chen *et al.* [11] had carried out the heartbeat classification based on projected and dynamic features of the ECG signal. The classification performed using SVM offered better classification performance. However, this technique botched to determine the ECG signals in the compressed domain.

2.1 Challenges

Few challenges existing in the arrhythmia classification are as follows:

- The major challenge while classifying the heartbeats is that temporal and morphological characteristics of the ECG signals are different for different patients [12].
- Most of the existing classification models used for classifying the heartbeats generates inaccurate results due to misclassification that occurs due to the large deviation in the training samples [10].
- Non-parametric modeling is one of the common techniques followed by ECG signal processing [13]. However, large order results in failure of impulse response modeling due to the attention required to be provided for small interval modeling during the interpretation [8].

3. Optimized SVNN for the Arrhythmia Classification

The automated technique of arrhythmia classification proposed using the optimized machine learning approach is discussed in this section. As machine learning is a promising mechanism for the prediction and classification, a technique based on SVNN classifier, named CS-SVNN, is proposed for the arrhythmia classification using ECG signals. The ECG pattern holds QRS complex, T wave as well as P wave. The shape and interval of the waves, namely PP, RR, PR, QT, and R peak could identify and evaluate the heart diseases. From irregularity in the heart rate and nature of the ECG signal, the diagnosis of the arrhythmia can be done. Initially, the wave features are extracted from the ECG signals in the patient record. The wave features together with the Gabor features from the feature vector, which is subjected as the input to the proposed CS-SVNN for the arrhythmia classification. The proposed CS-SVNN is introduced by the usage of CSO as the training algorithm in SVNN so that the weights and the biases are determined optimally. The block diagram of the proposed CS-SVNN based arrhythmia classification is depicted in Fig.1.

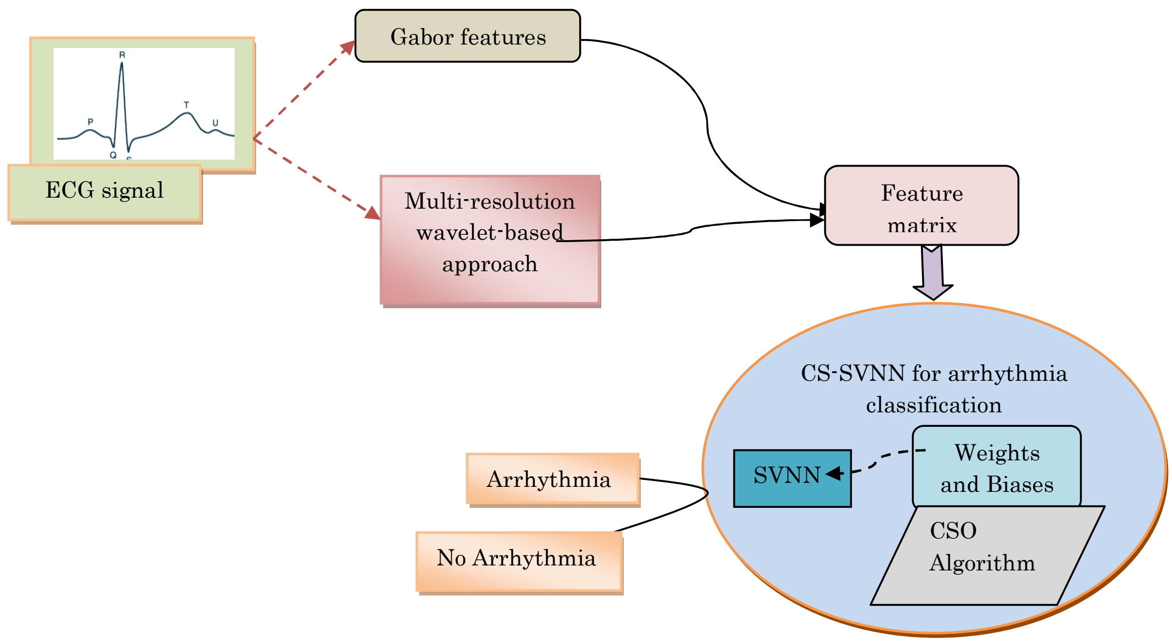

Fig 1. *Diagrammatic representation of the arrhythmia classification technique by the proposed CS-SVNN*

Let the database containing the patient records be represented as

$$P = \{P_1, P_2, ..., P_i, ..., P_m\} \tag{1}$$

where, m is the total number of patients, and the ECG signal of the i^{th} patient is denoted as $S^i_{1\times n}$.

3.1 Extraction of Wave Features

This section explains the feature extraction process, wherein the features from multi-resolution wavelet-based technique and statistical features are extracted. The multi-resolution wavelet-based method [15] applies eight-level decomposition to the input ECG signal, represented as $W[S^i]$, finding the eight wavelet levels. The QRS complex comprises of lower frequencies and thus, the higher degree of the decomposition level from the ECG signal is treated as the low-frequency components. The result of applying the wavelet decomposition is represented as,

$$\left[b^i_1, b^i_2, ..., b^i_8\right] = W\left[S^i\right] \tag{2}$$

where, $b^i_1, b^i_2, ..., b^i_8$ indicate the coefficients of the reconstruction wavelets. To detect the ECG waves, the wavelet coefficients are selected initially and the R peak is detected. Then, the Q and the S points are evaluated based on the five-point differentiation concept, followed by the wavelet coefficients of the S and T points. As the energy of the GRS complex is based on the third, fourth, and fifth component levels, they constitute the reconstructed wave to detect the QRS complex. Once the R peak is identified, the Q and the S waves are detected. The T and P waves are detected using the sixth and the seventh reconstruction coefficients. The feature matrix is constructed from the PR interval, PP interval, R peak, RR interval, and QT interval. The procedure for the detection of wave components and the feature matrix construction is the same as that followed in [10].

3.2. Feature Extraction Exploiting the Gabor Filter

After the generation of wave features, the statistical features are extracted by applying the Gabor filter. For the ECG signal provided, the Gabor filter is applied to extract the statistical features, like mean, variance, energy, standard deviation, skewness, entropy, and kurtosis. The Gabor filter is one of the bandpass filters that are used for extracting the texture feature. The purpose of choosing the Gabor filter for the feature extraction is due to its major advantage of posing the ability to represent the optimal properties of the ECG signal in the spatial domain as well as in the time domain. Moreover, the filter could mitigate the uncertainties that occur in time and space. The application of the Gabor filtering is and the features extracted are represented in the below equations,

$$I_i = G\left[S^i\right] \tag{3}$$

$$Y^i = \left\{I_M^i, I_V^i, I_E^i, I_{En}^i, I_S^i, I_{Sk}^i, I_K^i\right\} \tag{4}$$

where, $I_M^i, I_V^i, I_E^i, I_{En}^i, I_S^i, I_{Sk}^i, I_K^i$ are the mean, variance, energy, entropy, standard deviation, skewness, and kurtosis, corresponding to the i^{th} patient, after subjecting the input signal to the Gabor filter.

The final feature matrix is comprised of the features from the time intervals of the QRS complex wave and the statistical features extracted using the Gabor filter and the ECG waves from the multi-resolution wavelet-based method. Thus, the feature vector constructed is,

$$F^i = \left[X^i, Y^i\right] \tag{5}$$

where, X^i represents the time interval that has the dimension of [1x5], and indicates the Gabor features of dimension [1x7]. Thus, the feature vector constitutes the dimension of [1x12] for each patient.

3.3 CS-SVNN: SVNN with Cat Swarm Optimization based Training for the Arrhythmia Classification

In this section, the proposed CS-SVNN, exploited for the classification, is detailed. SVNN [14] was developed as an improvement of NNs to enhance the classification margin by following the procedure of SVM. SVNNs are learned using a Genetic Algorithm (GA), which is a simple heuristic algorithm. As GA is a traditional algorithm, it is replaced by one of the recent and better Swarm Intelligence approach, CSO [16] so that the performance of the classifier can be improved. Based on the input feature vector, the proposed CS-SVNN performs the arrhythmia classification. SVNN consists of three layers, such as the input layer, hidden layer, and output layer. The input layers hold a number of neurons, which are equivalent to the size of the feature vector. Between the layers are the weights and the biases that are determined using the training algorithm, CSO. Hence, the output of the SVNN is formulated as,

$$O = w_h \times \log sig\left[\left(\sum_{k=1}^{12} F_k^i * w_k\right) + b_1\right] + b_2 \tag{6}$$

where, w_h indicates the weights between the hidden and the output layers, w_k are the weights between the input and the hidden layers, b_1 and b_2 are the biases at the input and the output layers, and F_k^i represents the k^{th} feature, respectively.

Training Phase: The training of the SVNN is carried out using the CSO algorithm, which is inspired by the behavior of cats while hunting. The hunting procedure of the cat involves two modes, namely seeking and tracing modes. The seeking mode depends on the resting behavior of the cats, while the latter is during the chasing of the prey. Here, the position of the cats is adjusted until they reach the target or the prey. Here, a solution has the dimension of $[1 \times 15]$, denoting the number of the weights and the biases. The steps involved in the training procedure are:

i) Initialization: The primary step is the initialization of the population of cats, which is equivalent to the size of the solution vector. The population of the solution is expressed as,

$$Z = \{Z_1, Z_2, \ldots, Z_j, \ldots, Z_p\} \tag{7}$$

where, Z_j is the j^{th} solution, and p denotes the size of the population.

ii) Fitness Evaluation: The fitness of the solution is determined based on the error, which is required to be in minimum, as defined below:

$$f = \delta_{Max} + \delta_{Min} + \frac{c}{x}\sum_{i=1}^{x}\left|O_i - O_i\right| \tag{8}$$

where, O_i indicates the ground truth data, O_i denotes the estimated output, x indicates the total number of the training samples and c is regularization factor.

$$\delta = \mathrm{Eigen}\left(w \times w^T\right) \tag{9}$$

$$\delta_{Max} = \max(\delta)\,;\, \delta_{Min} = \min(\delta) \tag{10}$$

iii) Weight update: The weights of the SVNN are updated using CSO following the seeking mode or the tracing mode. The update equation of the CSO in the seeking mode depends on a parameter, "Seeking Range of The Selected Dimension" (SRD) and thus, the update is,

$$Z^{t+1} = \left(1 \pm Z^{SRD} \times r_1\right) \times Z^t \tag{11}$$

where, Z^t indicates the current solution, and Z^t is the random number between 0 and 1. Meanwhile, the position update of the cats in the tracing mode depends on the velocity of the cats. Thus, the position of the cat is changed based on the velocity as,

$$Z^{t+1} = Z^t + V^t + r_2 \times a\left(Z^{best} - Z^t\right) \tag{12}$$

where, V^t is the velocity of the cat at the current iteration, r_2 is the random number [0,1], refers the best solution, and a is a constant.

iv) Finding the optimal solution: Once the solution is updated, the fitness of the solution is computed again and the solution with the best fitness is kept in each iteration.

v) Termination: The above steps are repeated until the maximum iteration is reached and the best solution determined is selected as the feasible weights and biases.

Testing Phase: When the test signal is offered to the CS-SVNN classifier, based on the training done, the output of the CS-SVNN is determined. As it is a binary classifier, CS-SVNN generates an output 1, indicating the person as arrhythmia patient and normal in the other case.

4. Results and Discussion

This section explains the results of the proposed CS-SVNN classifier developed for the arrhythmia classification.

4.1 Experimental Setup

The proposed technique is executed in MATLAB in a system configured with Windows 10 OS, 2 GB RAM, and Intel core processor.

4.2 Database Description

The experimentation is carried out using two databases, namely the MIT-BIH Arrhythmia Database [17] and the MIT-BIH Normal Sinus Rhythm Database [18]. The database used in [17], is obtained from Boston's Beth Israel Hospital, which includes 48 half-hour excerpts of ECG recordings of 47 persons. The data is collected in the years 1975 and 1979 and has 360 samples per second in each channel. The range of the samples is 10 mV and has 11-bit resolution. The database [18] includes 18 long-term ECG recordings that are attained from the Arrhythmia Laboratory situated at Boston's Beth Israel Hospital.

4.3 Performance Metrics

The performance of the proposed technique is performed by three measures, namely accuracy, sensitivity, and specificity.

i) Accuracy: It refers to the measure of correctness of the classifier,

$$\mathrm{Accuracy} = \frac{TN + TP}{TN + TP + FN + FP} \tag{13}$$

where, " TP is true positive, FP is false positive, FN is false-negative and TN is true negative".

ii) Sensitivity: It indicates the true positives, which are exactly identified.

$$\mathrm{Sensitivity} = \frac{TP}{TP + FN} \tag{14}$$

iii) Specificity: the true negatives, which are precisely determined, denote the specificity.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{15}$$

4.4 Performance Analysis

The performance of the proposed technique analyzed by the data from the MIT-BIH Arrhythmia database, based on the three metrics is discussed in this section. The analysis is carried out using the statistical + CS-SVNN, biomedical + CS-SVNN, and hybrid + CS-SVNN, as presented in Table 1, with the population size as 700. Here, hybrid features denote both the biomedical and the statistical features. As presented in Table 1, the maximum performance attained is when the training percentage is kept in maximum. Hence, as the classifier is trained with more samples, the results attained can be improved. Initially, when the training data is 40%, the accuracy obtained by means of biomedical, statistical, and hybrid features is 0.9619, 0.796, and 0.785, correspondingly. For 80% training data, the accuracy obtained by CS-SVNN when the biomedical features alone are used is 0.9781, for the statistical features and the hybrid features; the accuracy is 0.954 and 0.986. Meanwhile, for the same training percentage, the sensitivity, and the specificity attained using the hybrid features is 0.99 and 0.968, respectively. Thus, it is clear that when both the features are used, the proposed technique has increased performance and thereby, performs the classification effectively.

Table 1. *Performance analysis of the proposed method*

Metrics	Training Percentage (%)	Statistical + CS-SVNN	Biomedical + CS-SVNN	Hybrid + CS-SVNN
Accuracy	40	0.796	0.9619	0.785
	50	0.812	0.9654	0.956
	60	0.858	0.9724	0.974
	70	0.93	0.975	0.977
	80	0.954	0.9781	0.986
Sensitivity	40	0.759	0.98	0.856
	50	0.826	0.981	0.982
	60	0.883	0.983	0.984
	70	0.951	0.9853	0.983
	80	0.974	0.986	0.99
Specificity	40	0.928	0.935	0.839
	50	0.934	0.942	0.871
	60	0.938	0.948	0.92
	70	0.942	0.953	0.958
	80	0.946	0.954	0.968

4.5 Methods Exploited for the Performance Analysis

The performance of the proposed technique is compared with five existing methods, such as KNN [8], NN [20], Fuzzy Subtractive Clustering [21], SVNN [19], and GB-SVNN.

4.6 Performance Analysis

In this section, the performance analysis of the proposed CS-SVNN with the existing techniques mentioned in section 4.5 is discussed. Table 2 summarizes the performance analysis of the approaches taken for the comparison, by varying the training percentage from 50 to 90. The performance increases with the increasing training percentage. While the training data is 50%, the accuracy attained by SVNN is 0.6429, when that of the proposed CS-SVNN is 0.734. Increasing the training data to 90% yields an accuracy of 0.8788 for KNN and fuzzy subtractive clustering. Meanwhile, the proposed CS-SVNN has an accuracy of 0.984. The sensitivity achieved by NN, KNN, SVNN, fuzzy subtractive clustering, and GB-SVNN is 0.96, 0.95, 0.637, 0.97, and 0.99, correspondingly, when the training data is 80% and 90%. Similarly, the specificity obtained by the existing NN, KNN, fuzzy subtractive clustering, and GB-SVNN is 0.875, 0.9167, 0.8333, and 0.9583, for the maximum training data percentage considered. However, the proposed CS-SVNN has a maximum sensitivity of 0.995 and specificity of 0.967. Hence, the maximum performance attained by the proposed technique compared to the conventional techniques reveals that the proposed CS-SVNN overcomes the conventional methods.

Table 2. *Performance analysis of proposed method*

Metrics	Training Percentage (%)	SVNN	KNN	GB-SVNN	NN	Fuzzy Subtractive Clustering	CS-SVNN
Accuracy	50	0.7143	0.6842	0.6429	0.5	0.5	**0.734**
	60	0.7143	0.7143	0.8571	0.5263	0.6923	**0.9**
	70	0.7273	0.7308	0.9474	0.5714	0.7895	**0.953**
	80	0.7308	0.8571	0.9615	0.6364	0.8462	**0.973**
	90	0.7369	0.8788	0.9697	0.7857	0.8788	**0.984**
Sensitivity	50	0.637	0.6175	0.6435	0.624	0.97	**0.687**
	60	0.637	0.6175	0.99	0.624	0.97	**0.994**
	70	0.637	0.7389	0.99	0.96	0.97	**0.994**
	80	0.637	0.95	0.99	0.96	0.97	**0.995**
	90	0.637	0.95	0.99	0.96	0.97	**0.995**
Specificity	50	0.9	0.6	0.8	0.6	0.5	**0.865**
	60	0.9	0.8	0.9	0.6	0.6	**0.92**
	70	0.9	0.8571	0.9286	0.7	0.7143	**0.9344**
	80	0.9	0.8947	0.9474	0.7143	0.7895	**0.9568**
	90	0.9	0.9167	0.9583	0.875	0.8333	**0.967**

5. Conclusion

This paper introduces an optimized machine learning technique, CS-SVNN, for the arrhythmia classification by means of ECG signals. Here, various features, such as biomedical features from the multi-resolution wavelet-based method and statistical features are extracted to create the feature vector. Finally, the proposed CS-SVNN, which is newly developed by the inclusion of CSO algorithm in the training algorithm of SVNN, is employed for distinguishing arrhythmia patients from normal persons. The effectiveness of the proposed approach is verified exploiting three performance evaluation metrics, namely accuracy, sensitivity, as well as specificity. The results attained are compared with that of the existing techniques, like SVNN, KNN, fuzzy subtractive clustering, NN, and GB-SVNN. Finally, the experimental results revealed that the proposed CS-SVNN has the outperformed the existing techniques with the maximum accuracy of 98.4%, sensitivity of 99.5, and specificity of 96.7%, as well as thereby, it is found to be effective for the arrhythmia classification.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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