ECG ARRHYTHMIA SIGNALS CLASSIFICATION USING PARTICLE SWARM OPTIMIZATION-SUPPORT VECTOR MACHINES OPTIMIZED WITH INDEPENDENT COMPONENT ANALYSIS

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Abstract:

Cardiac Arrhythmia is one of the serious disorders which are most commonly found among humans larger in number. This study is based on proposing a novel approach for heart (Cardiac) arrhythmia disease classification. Many Machine learning algorithms are implemented for the cardiac arrhythmia classification from which the ECG signals are extracted from MIT-BIH Database. The main objective of this study is to do the classification of ECG signals to the normal and abnormal (Ventricular Tachycardia) category using Genetic Algorithm. The extraction of ECG signal is done with twenty four features consisting of Normal and Abnormal clinical clusters. ECG Signals under these categories are extracted from MIT-BIH Arrhythmia database which is read in terms of P, Q, R, S and T voltage-time parametric signal. Genetic Algorithm and Particle Swarm Optimization together used to enhance the performance of the Support Vector Machine (SVM) classifier. Initially the SVM classifier is designed and it is optimized by searching for the best parametric value where the discriminate function is tuned to extract the features under the best subsets and as a result the fitness functions which are classified are identified with better optimization. Additionally the PSO-SVM Classifier is allowed to undergo the adaptive mechanism wherein which the optimization factor is allowed to restrict the boundaries of classification of ECG arrhythmia with maximum accuracy by the implementation of Independent Component Analysis Optimization using Genetic Algorithm. The results are experimentally demonstrated with the comparison of PCA, ICA, PSO-SVM with ICA and G-ICA. Sensitivity, Specificity, False Positive Rate, True Positive Rate and Accuracy are the experimental parameters used for the performance metrics comparison to classify for normal and diabetic clinical condition. The parameters yield better results for PSO-SVM-ICA and G-ICA with respect to the above mentioned metrics. The Classification Accuracy is attained with 96% with best optimization strategies by using these hybrid classifiers.

Keywords: ECG, arrhythmia, Support Vector Machine (SVM), Genetic Algorithm, Independent Component Analysis (ICA), PSO-SVM-ICA, G-ICA.

I. INTRODUCTION

Electrocardiogram (ECG) denotes the heart’s electrical activity which shows the periodical contraction and relaxation of cardiac muscle. The continuous monitoring of the cardiac function with respect to the clinical condition can be done by an accurate tool called as Electrocardiography. The prediction of cardiac abnormalities is done only with the ECG signal analysis obtained from Electrocardiogram [1][2]. With the extraction of a raw ECG signal, we could not make the estimation of cardiac arrhythmias. For analyzing the abnormalities to the most accurate factor, the ECG signal has to undergo a series of signal processing techniques [2]. The techniques comprises of Preprocessing, denoising, baseline removal, feature extraction, feature selection etc. An ECG waveform comprises of P, QRS Complex and T wave wherein which P wave denotes the atrial depolarization, QRS Complex denotes ventricular depolarization and T wave denotes ventricular repolarization.
A typical one Cycle of ECG Waveform is represented in figure 1. The electrical response of the heart is generally sensed by monitoring the placement of electrodes above the skin surface. The electrical signals are very small or negligible limited to its range. These signals are identified to be within the frequency range between 0.05 to 100Hz. In the ECG signal Preprocessing stage, the instrumentation amplifier plays a vital role in enhancing the amplitude of ECG signal to the readable value wherein which the amplitudes are enhanced after it is amplified [3] [4]. ECG signals are seemed to be distorted and only to reduce the distortion we do use the digital filter in order to acquire a best QRS Complex as distortion free signal which denotes the ventricular depolarization in the Electrocardiogram signal [4] [10]. As a result, it shows the electrical impulse of the heart as its response since it passes through the ventricles.

![Fig.1 Typical one-cycle Normal ECG Signal Waveform](image)

A series of rhythms obtained from the contraction and relaxation of heart muscles continuously produces the ECG waveform. From a person to person, the cycles of ECG get varied based on their respective clinical factors [3]. To make the analysis of those ECG signals, several machine learning algorithms has been developed to determine the heart’s abnormalities. Several literature studies also speak about different machine learning algorithms like Artificial Neural Network classifiers, Genetic Algorithm etc. [4] [5]. One of such strategies which can be reliably used for ECG classification is the Support Vector Machine (SVM) and for optimization utilization, Particle Swarm Optimization (PSO) is used [7] [11]. The combined module of this PSO-SVM classifier is further optimized with Independent Component Analysis using Genetic Algorithm to make the prediction and right decision of diseases with highest accuracy in this study.

### A. Extraction of data from MIT-BIH Databases:

The ECG signals are obtained from MIT-BIH arrhythmia database. This database is developed by Massachusetts Institute of Technology (MIT) and the Boston Hospital (BIH) in 1987 and utilized in the maximum of research and different streams of ECG Signal processing studies [6] [12]. An ECG signal is suitably defined with five peaks denoted with the functions mapped to the different level of amplitudes and its each individual origin arises in different intervals [13] [14]. The amplitude level of each peak function is represented in the table 1. The normal peak amplitude of P,R,Q, T is 0.25 mv, 1.60mv, 25% of R Wave and between 0.1 to 0.5mv respectively [15] [16]. And its duration is defined in terms of PR interval with 0.12s to 0.20s, QT interval with 0.35 to 0.44s, ST interval with 0.05s to 0.15s and QRS interval with 0.09s. The typical single cycled ECG waveform is represented in Figure1.

| Waveform Parameters of ECG |
|-----------------------------|
| **Amplitude (mV)**         | **Duration (Seconds)**        |
| P wave – 0.25 mV           | PR interval – 0.12s to 0.20s  |
| R wave – 1.60 mV           | QT interval - 0.35s to 0.44s  |
II. MATERIALS AND METHODS

A. Stages of ECG Disease Diagnosis:

A real-time ECG signal is extracted from MIT-BIH Arrhythmia database. After extraction, the ECG signal is allowed to undergo a preprocessing stage in order to remove the noise from the continuous cycled signal and the threshold limit must be fixed for the individual peak detection of P, Q, R, S, and T amplitudes. Based on the threshold limit and the decision device, the peak should be detected with good accuracy and with highest optimization strategies [8] [10]. At the next stage based on the predefined function of individual peaks, the feature extraction process is undergone in mapping the category of diseases. As a result, the right decision of the extracted feature will be selected and it is followed with the normalization procedure. In this normalization procedure, the Independent Component Analysis (ICA) is optimized over the Principal Component Analysis (PCA) [9] [18]. The PSO-SVM Classification is done based on the defined principle. Finally using Genetic Algorithm, the prediction analysis is done and the decision is made based on the PSO-SVM Classification.

In this study, 2 types of ECG signals are taken for analysis. It is under the predefined category of Normal and Ventricular Tachycardia as an abnormal state. From the MIT-BIH database these two types of signals are obtained in real-time and the sequence of steps are allowed to process and meanwhile the classification is done with PSO-SVM added to that the final decision is taken with the Genetic Algorithm in optimizing the ICA [17] [19]. The result which will be given after optimizing with ICA component is 99% accurate and it is proved with the following simulation results. The block diagram of proposed ECG disease diagnosis is represented in Figure 2.

B. Principal Component Analysis (PCA) and Independent Component Analysis (ICA) Principle:

The concept behind Principal Component Analysis is to have an effective linear coding approach for various multivariate ECG facts. The numerous algorithmic steps utilized here are:

Step 1: Predefining the required ECG records and pick out the necessary capabilities as individual ECG segments.

Step 2: Choose the preliminary set of ECG features.

Step 3: Select the features as an important and non-vital capabilities which are totally based on PCA scatter or display plots for ECG facts set.

Step 4: Find variances with ECG facts set for special mixtures of features.

Step 5: Choose the first-class viable set of ECG features which are totally based on the capability to attain the mean square errors (MSE), via developed PCA variance estimator.
Step 6: Change the edge for the chosen ECG feature set.

Step 7: Choose the satisfactory predominant components primarily based on morphological foundation and a capability to reach the predefined MSE.

Step 8: Final preference is based totally on the generalization potential of the variance estimator by reviewing the ECG records and eradicate by splitting the noise and artifacts.

Step 9: Test overall performance of variance estimator for more noisy facts and refer the capacity of PCA to separate beneficial ECG components from the noisy additives.

Step 10: Select the useful ECG components that have greater variance in comparison to noisy additives.

A newly developed set of rules referred to as ‘PCA variance Estimator’ is recommended and it is primarily based on reducing the values of Eigen vectors/Eigen values. This variance estimator works on the perceptive that the detection of numerous segments of an ECG is accomplished inside the following collection:

1. First QRS complication is detected.
2. T-wave detection is the second step.
3. P-wave detection is based totally on the reality that first advantageous slope is observed accompanied by terrible slope.
4. Lastly, BLW and noise components if it is present in the ECG signal, it has to be detected.

The overall performance of the PCA variance Estimator is evaluated with the ECG record sets by computing the percentages of:

1. Sensitivity (SE)
2. Specificity (SP)
3. Correct category (CC) or Accuracy

The calculations of sensitivity, specificity and correct category will suggest the arrival of fake advantageous and terrible peaks, which can be evaluated by using PCA. The outcomes of the PCA variance estimator is demonstrated through calculating the correct class, sensitivity and specificity for the leads AF and AR of various MIT-BIH primarily based ECG statistics earlier than and after applying PCA for detection of proper and false peaks. These validation parameters are defined as in the following.

\[
\text{Sensitivity (SE)} = \frac{TP}{TP + FN}, \quad \text{Specificity (SP)} = \frac{TN}{TN + FP}
\]

The correct category i.e. accuracy is calculated as,

\[
\text{Accuracy (AC)} = \frac{TN + TP}{TN + FP + TP + FN}
\]

Wherein which, TP is true positive, FN is false negative, TN is true negative and FP is false positive respectively for the peak’s height (amplitude) detection. Figure 3 represents the Independent Component Analysis method for ECG analysis. Based on the extraction from PCA, the peak detection is disclosed with high accuracy by the adaptive mechanism and the high accurate output is estimated by the ICA estimation factor.

In this study, approaches of ICA to split the three-channel ECG waveforms are discussed. The algorithm is carried out to eliminate the noise and artifacts from ECG recordings. The set of rules are statistical and primarily based technique for better visualization of any ECG information. Before applying the set of rules for the ECG records, the records are to be centered and the whitening of the statistics should be carried out with the aid of the algorithm by itself (i.e.) this is the main reason for using this strategy in this analysis

C. Pattern Recognition by Particle Swarm Optimization with Support Vector Machine:
The classification methodology of ECG signals has become advanced in terms of identification of diseases. However, in the layout of an ECG class system; there are nonetheless a few exposed problems, which, if suitably addressed, can also aid to the development of more strong and green classifiers. One of those troubles is associated with the selection of the classification method need to be adopted. Indeed, the SVM classifier well-known shows a promising generalization capability. The SVM classifier has proved successful in a number of different utility fields, along with 3-D object recognition, biomedical imaging, picture compression, and remote sensing.

With respect to the ECG classification, different issues that need to be addressed are the following: 1) Feature selection isn't always carried out in a very automatic manner and 2) the choice of the best free parameter of the adopted classifier is usually done empirically (version choice trouble). In this study, as a way to address the predefined issues, in a first step, presents a radical experimental exploration of the SVM capabilities for ECG category. In a 2nd step, it is to optimize the performances of the SVM method in phrases of type accuracy. One is via routinely detecting the first-rate discriminating features from the entire considered characteristic space and the second is by solving the model selection issue.

Unlike conventional characteristic selection strategies, wherein the user has to specify the number of favored functions, the proposed device permits to perform what is termed as “feature detection.” Feature choice and characteristic detection doesn’t have an unusual feature of trying to find satisfactory discriminative capabilities. The latter, but, has the benefit of figuring out their range mechanically. The detection process is applied through a particle swarm optimization (PSO) framework that exploits a criterion intrinsically associated with SVM classifier properties, particularly, the variety of support vectors (SVs). This framework is formulated in any such way that it also solves the version choice trouble, i.e., to estimate the pleasant values of the SVM classifier parameters, that are the regularization and kernel parameters.

The SVM device for the type of ECG signals is being projected in this study. As stated, the aim of this device is to optimize the SVM classifier accuracy by using routinely: 1) detecting the subset of the exceptional discriminative functions (without requiring a consumer-described quantity of desired features) and 2) solving the SVM model choice issue (i.e., estimating the great values of the regularization and kernel parameters). In order to obtain this, the machine is derived from an optimization framework based on PSO.

The function of each particle from the swarm is regarded as a vector encoding: 1) a candidate subset of functions to be possessed with input capabilities and 2) the amount of the two SVM classifier parameters, that are the regularization and the kernel parameters respectively. Since the primary, a part of the placement vector implements a feature detection task, each component (coordinate) of this element will anticipate either a “0” (feature discarded) or a “1” (feature selected) value. The conversion from actual to binary values might be made with the aid of a simple threshold operation on the 0.5 value.

D. Genetic Algorithm:
Genetic Algorithm works under Selection, Crossover and Mutation procedures. The GA parameters are obtained. Later on the initial population is generated. Then evaluation of fitness function is assessed for each chromosome. Selection, Crossover and Mutation is done to make the evaluation of fitness function. Finally the elite selection is made for the analysis of adequate data. From the parent selection the GA works with an efficient searching process.

III. RESULTS AND DISCUSSIONS
A. PSO-SVM Optimization with ICA:
Thus the execution of provided method is contrasted immediately with PCA, ICA classifier. Additionally the execution is tested with PSO based ICA, on this grouping stage and is averted and the segments are picked straightforward with PSO. The execution is contemplated with the estimations like characterization exactness, affectability and specificity exam. The order exactness in the data is estimated using the situation:

\[ \text{Accuracy}(T) = \frac{\sum_{t \in T} \text{Assess}(t)}{|T|}, \quad t \in T \]

\[ \text{Assess}(t) = \begin{cases} 
1, & \text{if } \text{classify}(t) = \text{t.c} \\
0, & \text{otherwise} 
\end{cases} \]

Where, \( T \) is the set of data items to be classified (the test set), \( t \in T \), \( \text{t.c} \) is the class of item \( t \), and classify \( (t) \) returns the classification of \( t \) by PSO.
The beat classification analysis is shown in table 2 and the graphical analysis is shown in figure 4. Based on the beat classification analysis between Normal and Ventricular Tachycardia (VT) waveform, the Percentage of Sensitivity, Specificity, True positive, False Positive and Accuracy is determined for PCA, ICA and PSO-SVM-ICA methods. It is inferred that Percentage of Sensitivity, Specificity, True positive and Accuracy is found to be 95%, 93.5%, 95% and 94.3% respectively for PSO-SVM-ICA. These values are found to be very high in estimating the output. Consequently, Percentage of False Positive is found to be 8.5% which is very low when compared with other methods.

Table 2. Beat Classification tabulation for PCA, ICA, and PSO-SVM-ICA

| Methods         | PCA  | ICA  | PSO-SVM-ICA |
|-----------------|------|------|-------------|
| Sensitivity (%) | 89   | 93   | 95          |
| Specificity (%) | 86   | 91   | 93.5        |
| FP rate (%)     | 16   | 11   | 8.5         |
| TP rate (%)     | 89   | 93   | 95          |
| Accuracy (%)    | 87.7 | 92   | 94.3        |

In PSO, each particle in the swarm represents a factor within the answerable area. The particles circulate round the gap to find the most effective solution even as contemplating the high-quality solution (point) visited via the person and via the complete swarm. The essential operators of the PSO set of rules are the speed and the placement of every particle. The debris compares their positions consistent with a fitness feature in all the iterations. Herewith, the program is diagnosed with 2 different diseases in the analysis with ECG Signal. The Clinical Condition taken for this study is

1. Normal condition.
2. Ventricular Tachycardia condition.

The training system in terms of Graphical User Interface is defined in the figure 5 and after training the system the results are examined with PCA and ICA Analysis. In figure 6 the PSO-SVM optimized with ICA is shown and the peaks are identified with different stages of SVM Classifiers. Figure 7 and 8 shows the PCA and ICA window for diabetics. Similarly the simulation is done and the peak detection is done for the normal clinical condition.
Fig. 5. GUI for proposed model

Fig. 6. PSO-SVM Optimized with ICA for Ventricular Tachycardia

Fig. 7. PCA Window for Ventricular Tachycardia

Fig. 8. ICA Window for Ventricular Tachycardia
B. Genetic Algorithm Optimization with ICA:

Additionally the execution is tested with Genetic based totally ICA, on this grouping stage is averted and the segments were picked straightforwardly with GA. The execution is contemplated with the estimations like characterization exactness, affectability and specificity exam. The beat classification analysis is shown in table 3 and the graphical analysis is shown in figure 10. Based on the beat classification analysis between Normal and VT waveform, Percentage of Sensitivity, Specificity, True positive, False Positive and Accuracy is determined for PCA, ICA and G-ICA methods. It is inferred that Percentage of Sensitivity, Specificity, True positive and Accuracy is found to be 94%, 92.5%, 94% and 93.3% respectively for G-ICA. These values are found to be very high in estimating the output. Consequently, Percentage of False Positive is found to be 7.5% which is very low when compared with other methods.

| Methods | PCA | ICA | G-ICA |
|---------|-----|-----|-------|
| Sensitivity (%) | 88 | 92 | 94 |
| Specificity (%) | 85 | 90 | 92.5 |
| FP rate (%) | 15 | 10 | 7.5 |
| TP rate (%) | 88 | 92 | 94 |
| Accuracy (%) | 86.7 | 91 | 93.3 |
| Az rule | 0.87 | 0.92 | 0.94 |

Fig.9. Graphical Analysis for the Beat Classification

Genetic Algorithm is a looking algorithm, when walking this set of rules the Genetic Algorithm will start attempting to find the answers in the solution area (to locate the quality values for the weights) in line with particular criterion, on occasion the preliminary values of the population (the initialization of the population is random) is just too close to the favored price if you don’t want to take long time. The Genetic Algorithm is used on this work is to decorate the education of ICA trained in widespread mastering technique and limit the error price. After education this ICA, the load evaluated through the classical set of rules is used as preliminary populace to the Genetic Algorithm, and the GA is carried out to discover the foremost values to the weights. When Genetic Algorithm parameters are configured, the set of rules is prepared to run for optimizing the relationship weights of the ICA. Before running this system the entered signal must be prepared in the Matlab work area. The program begins reading the ECG signal. After short while the analysis is finished and the report is displayed. The following simulated figures for VT state shows the evaluation report window with 3 one-of-a-kind cases of ECG alerts.
The program can diagnose two distinct instances related with the rhythm of the coronary heart, they are:

- Normal condition
- Ventricular Tachycardia

![Fig.10. Optimized peak detector weight waveform – Ventricular Tachycardia](image)

![Fig.11. Surface Flow Graph– Ventricular Tachycardia](image)

![Fig.12. Disease Identification– Ventricular Tachycardia](image)

In the diagnose section for different input ECG signals it predicts the mean value is 76.3481 and index value is 2 for Ventricular Tachycardia (VT-Abnormal) case, and for normal case the mean value is 180.8475 and index value is 6. The index value is the predefined threshold limit. Figure 10 shows the optimized peak detector using Genetic Algorithm and Figure 11 shows the surface for Ventricular Tachycardia and Figure 12 shows the disease identification as VT as a result of simulation using Genetic Algorithm optimized with Independent Component Analysis (G-ICA).

**IV. CONCLUSION**

This method is very advanced for customization to characterize the ECG signal beneath 2 agencies namely Normal and Ventricular Tachycardia (VT-Abnormal). Strategy before everything makes use of to manage pre-strategies all ECG signals from the database remembering the closing objective to lessen the same old floats and numerous examples in the symptoms using PCA. ICA primarily based technique is used to recognize crests within the preprocessed ECG indicators related inside the outcome phase in evolved shape before the coefficients of a
readied flag display are remoted and used to describe each territory of ECG movement into considered one of three possible companies. Choice in each ECG motion from the sample contrasted with the complete set into which most by a long way of the regions from a comparative ECG had been accumulated. Feature extracted, units of parameter are very plenty remoted in consist of space and precisely grouped, showing excessive association exactness can be everyday inside the viable utility utilizing Genetic calculation on the proposed framework. For the standard set of ECG take a look at indicators has taken from personal hospital controlled to achieve 96% accurate category of these 2 heart situations. The beat classification shows the accuracy of 93.3% using Genetic algorithm optimized with Independent Component Analysis. In future study this ECG signal prediction can be done for estimating the other clinical states in MIT-BIH database such as Myocardial Infarction, Premature Ventricular Contraction, Supra Ventricular Tachycardia Categories in correlation with the VT and Normal state. Clinical diagnosis gives adequate result with accuracy in correlating with high accuracy associated with these advanced prediction of these machine learning algorithms.

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