Journal of Intelligent Systems and Internet of Things
Vol. 13, No. 01, PP. 71-82, 2024
DOI: https://doi.org/10.54216/JISIoT.130106

An Improved Internet of Thing-based Optimized SVM Approach for ECG-founded Cardiac Arrhythmia Classification

Yogendra Narayan Prajapati[1], Beemkumar N.[2], Mary Christeena Thomas[3], Lovish Dhingra[4], Rishabh Bhardwaj[5], Aws Zuhair Sameen[6]

[1] Assistant Professor CSE, Ajay Kumar Garg Engineering College, Ghaziabad, U.P. India
[2] Professor, Department of Mechanical Engineering, Faculty of Engineering and Technology, JAIN (Deemed-to-be University), Bangalore, Karnataka, India
[3] Assistant professor ,Ece Vel Tech Rangarajan ,Dr.Sagunthala R&D Institute of Science and Technology Avadi, Chennai, Tamil Nadu
4 Centre for Research and Development, Chitkara University, Himachal Pradesh-174103 India
[5] Centre of Research Impact and Outcome, Chitkara University, Rajpura- 140417, Punjab, India
[6] College of Medical Techniques, Al-Farahidi University, Baghdad, Iraq
Emails: ynp1581@gmail.com; n.beemkumar@jainuniversity.ac.in; marychristeenathomas@veltech.edu.in; lovish.dhingra.orp@chitkara.edu.in; rishabh.bhardwaj.orp@chitkara.edu.in; aws.zuhair@uoalfarahidi.edu.iq;

Abstract

Cardiovascular diseases (CVD) stand as the leading cause of global mortality, claiming millions of lives annually. An electrocardiogram (ECG) records the heart's electrical activity based on the Internet of Things (IoT), crucial in detecting cardiac arrhythmias (CA), characterized by irregular heart rates and rhythms. Signals from the MIT-BIH Arrhythmia Physio net database are analyzed. This chapter aims to propose a hybrid approach merging Genetic Algorithm-Support Vector Machine (GSVM) and Particle Swarm Optimization-Support Vector Machine (PSVM) for CA classification. The study introduces an algorithm for categorizing ECG beats into six groups using Independent Component Analysis (ICA)-derived features. Optimal SVM settings are determined using Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) on ICA features computed via non-parametric power spectral estimation. The research delves into the origins and methodologies of GA and PSO. Simulation results comparing GSVM and PSVM are presented, emphasizing PSVM's superior performance in accuracy, sensitivity, specificity, and positive predictivity. Detailed performance metrics, including Sensitivity, Specificity, Positive Predictivity, and Accuracy percentages, are scrutinized and compared against the top classifier. The findings endorse PSVM's superiority over GSVM, indicating enhanced performance across multiple evaluation criteria.

Received: August 19, 2023 Revised: November 18, 2023 Accepted: May 12, 2024

Keywords: PSO; ICA; IoT; SVM; CA; GA;

1. Introduction

Electrocardiography, often known as an electrocardiogram, is a technique for recording the heart's electrical activity over time by attaching electrodes to the skin at certain locations. With the use of these electrodes, the electrophysiological pattern of depolarization and repolarization in the heart muscle that occurs with each heartbeat may be detected [1]. The usual reason for doing so is to perceive heart complications.

The electric capacity of the heart is then measured from 12 separate vantage points ("leads") and recorded over some time (often 10 seconds). In this way, the basic significance and course of electrical depolarization of the heart are captured at each moment in a very small number of phases of the cardiac cycle [2].

Figure 1 depicts the anatomy of the heart, which consists of the left atrium, the right atrium, the left ventricle, and the right atrium, as well as the atrioventricular node and the sinoatrial node. The atria (upper chambers) are labelled as left and right, whereas the ventricles (lower chambers) are labelled as left and right [3]. Fibrous, non-conductive tissue connects the atria to the ventricles, creating an electrical barrier between the two chambers of the heart. The right atrium and right ventricle work as a pump to move blood to the lungs. The superior and inferior vena cava are bigger veins that carry oxygen-poor blood away from the heart and into the right atrium [4]. The right ventricle can contract with more force once the right atrium contracts, stretching it and forcing blood into it. The next step in completing oxygenation is the pumping of blood to the lungs by the right ventricles. The same holds for the return of oxygen-rich blood from the lungs to the rest of the body; this process involves the pulmonary veins, the left atrium, and the left ventricle [5].

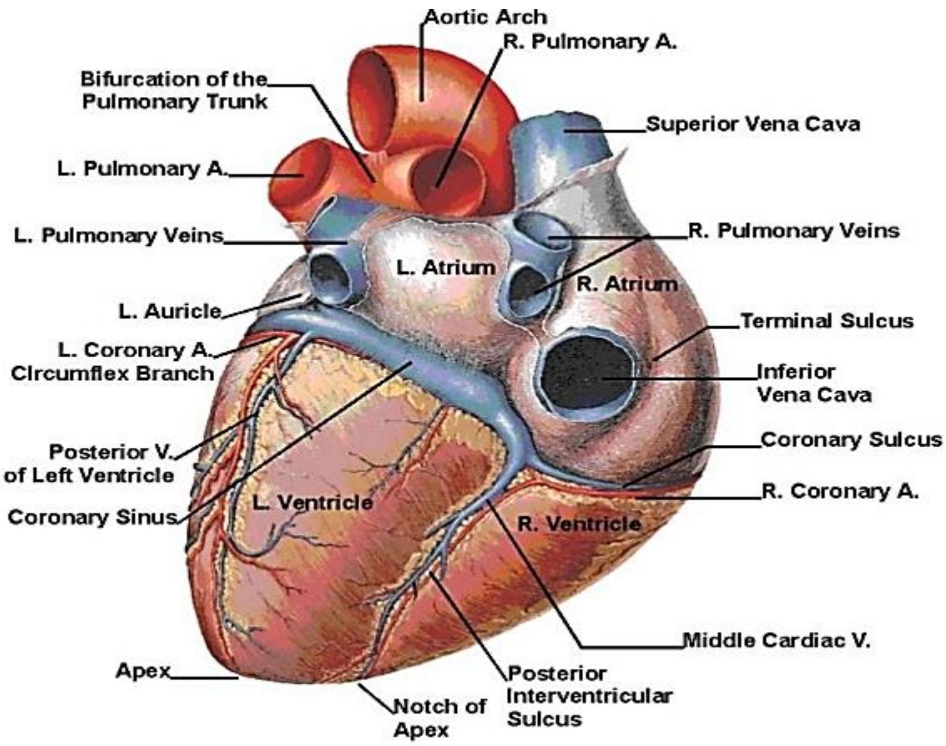

Figure 1: The Human Heart Anatomy [Google].

By keeping tabs on the patient, an electrocardiogram (ECG) can be quickly and painlessly analyzed. The patient's heart rate is monitored using ECG equipment while they are in touch with a small number of leads [6]. With its strong classification skills, Support Vector Machine (SVM) is perfect for identifying intricate patterns in arrhythmia data. When it comes to feature selection and model optimization, SVM is at its best when optimized with algorithms like Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). While PSO effectively traverses parameter optimization by imitating social behaviour, GA explores a wide solution space using methods inspired by evolution. Arrhythmia detection relies on early diagnosis and intervention in cardiovascular disorders, which can save lives and improve patient outcomes. Their synergy with SVM guarantees superior classification accuracy, sensitivity, and specificity in this area.

We can identify the type of cardiac arrhythmias occurring in the patient by looking for specific signs. Different arrhythmias can be studied using this method because the P wave, QRS complex, and T wave components of the signal might vary [7]. The magnitude of the cardiac signal differential is determined by the wave's breadth and height. By dynamically selecting the characteristics of the subset, the Genetic Algorithm-Support Vector Machine (GSVM) classifier significantly impacts the ECG signal categorization, which in turn optimizes the SVM classifier [8]. The classification method prepares data with the discrete wavelet transform, reduces dimensionality with principal component analysis (PCA), and extracts features with independent component analysis utilizing non-parametric PSD estimation [9].

The classifier is allowed to take in these extracted features. Classifier accuracy is then calculated and used to verify the chromosome's fitness. Particle swarm optimization, or PSO for short, is a stochastic optimization method that takes its cues from collective behavior patterns, such as those seen in a flock of birds, a school of fish, or a community of humans [10]. For each cycle of SVM-trained values, PSO will establish the updated position and velocity of each particle in an iterative method.

2. Related Work

Many people have ventricular and atrial arrhythmias, which are among the most dangerous consequences of cardiovascular illness. These arrhythmias can cause irregular heartbeats [11]. Several authors have argued that ventricular arrhythmias such as flutter and fibrillation are fatal disorders that cause sudden cardiac arrest.

Due to its minute variation in amplitude and time duration, researchers have indicated that it is very difficult to extract and analyze the secret data present in ECG signals. As a result, recommendations are made for diagnoses that can be aided by software, and clinicians in subsequent therapy [12] can use the resulting data. The authors propose a classification-learning algorithm for identifying six different categories of ECG beats. The algorithm achieves an 86% sensitivity rate for APC beats and a 97% sensitivity rate for the other five types of beats. The research team has also suggested a machine learning method that can classify 5 distinct types of ECG beats with an accuracy of 93.97 percent. The investigators report an accuracy of 88.84% when applying the Particle Swarm Optimization and Wavelet Transform methods to the classification of six distinct ECG arrhythmias [13]. Consuming a neuro-fuzzy methodology and the Hermite Coefficients of beats in the ECG signal, the researchers were able to attain a 96% classification accuracy. The Gaussian Mixture Model (GMM) was used to classify two distinct abnormality states in the ECG data, with an accuracy of greater than 94%. Furthermore, the scientists have presented a wavelet transform and PCA-based SVM classifier model for ECGs, which research has revealed can differentiate between healthy and abnormal heartbeats with an accuracy of 95.6% [14].

The purpose of preprocessing is to improve the overall quality of the ECG for more accurate analysis and assessment. The ECG could be severely disrupted by noise, making it impossible to rely on the original signals for accurate measurements [15]. Most noise can be broken down into three broad categories based on frequency.

The elimination of strife like baseline wander and power line interference requires a narrowband filter, hence this design has received a lot of focus. The high spectrum overlap between the ECG and muscle noise makes removing the noise caused by muscular activity a much more challenging filtering challenge [16-18]. When necessary, approaches that take advantage of the fact that the ECG is a recurrent signal can be used to minimize muscle noise in the ECG. The frequency of a standard ECG signal varies between 0.05 and 100 hertz. The eradication of artifacts is a vital stage in ECG signal treatment [19-22]. If there are artifacts present in the data from the ECG, it will be easier for the specialist to diagnose the diseases. Any instrument that is intended to record ECG signals should strive to do so with as little background noise as is humanly practical. There are a variety of various approaches that can be taken to extract the ECG parameters from a noisy ECG signal [23].

The authors developed a technique utilizing Hidden Markov Models to analyze cardiac arrhythmias. This method includes approaches that examine ventricular arrhythmias by assessing the QRS complex and R-R durations [24-25]. Hidden Markov modeling aims to integrate the structural and statistical details of the ECG signal into a distinct parametric model. Ambulatory ECG recordings often feature low amplitude P waves, posing detection challenges. Hidden Markov modeling effectively addresses this issue [26].

3. Objective of the Research Work

This research paper will center on identifying and suggesting a hybrid approach, combining Genetic Algorithm-Support Vector Machine (GSVM) and Particle Swarm Optimization-Support Vector Machine (PSVM), for the classification of cardiac arrhythmias.

4. Research Question for the Research Work

- How effective are the hybrid Genetic Algorithm-Support Vector Machine (GSVM) and Particle Swarm Optimization-Support Vector Machine (PSVM) in classifying cardiac arrhythmias?
- What are the optimal parameters for achieving accurate classification results?

5. Goals of the Research Work

Develop a hybrid classification approach for cardiac arrhythmias leveraging GSVM and PSVM to enhance accuracy and efficiency.

6. Expected Contributions of the Research Work

Contribute a novel method for accurate cardiac arrhythmia classification, improving patient diagnosis and treatment outcomes.

7. The Proposed Work

In this analysis, we take advantage of the features generated by ICA. As was previously noted, the SVM classifier is used because it has proven effective in a variety of classification situations. One of the supporting features of the suggested method is the use of Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) to find the best possible settings for the SVM's parameters. High optimization is required for the penalty parameter C of the support vector machine (SVM), which is expected to be a positive integer, and the kernel parameter of the Gaussian radial basis function (GRBF), which is expected to be a positive real number. It is being analyzed how well the proposed ICAs built with non-parametric PSD estimation features extracted using the Genetic Algorithm-Support Vector Machine (GSVM) method and the ICAs built with non-parametric PSD estimation features extracted using the Particle Swarm Optimization-Support Vector Machine (PSVM) method perform.

In the realm of machine learning, the Support Vector Machine is a supervised technique. Specifically, SVM accomplishes cataloguing tasks by building Optimal Separating Hyper-Planes (OSH). The OSH widens the gap between the two adjacent data points that fall into distinct categories. Figure 2 depicts the results of using SVM to divide a dataset into two classes. If the hyperplane's margin grows, the ensuing inequality will be proven correct for all and all input data.

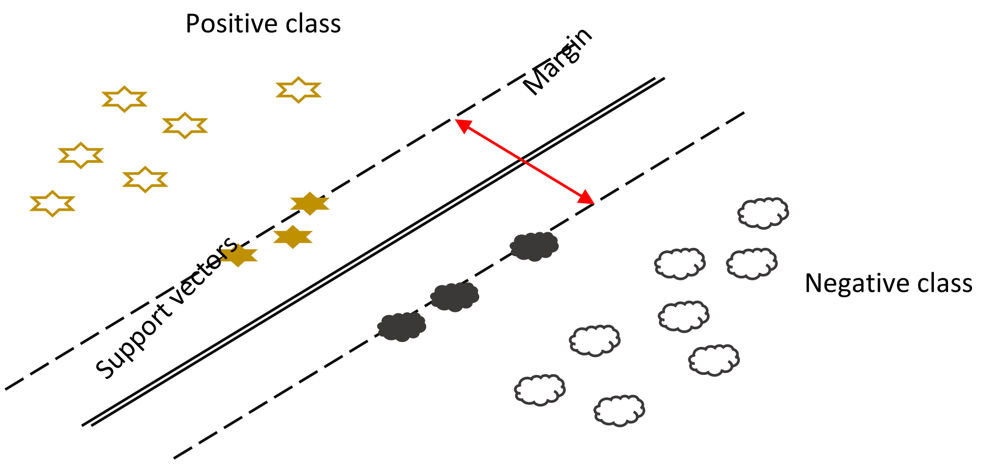

Figure 2: Divider of two classes by SVM.

The ECG data comes from the arrhythmia database at MIT-BIH. Denoising, detecting QRS peaks with DWT, normalizing; performing dimensionality reduction with PCA, and extracting features with

ICA are all part of the preprocessing stage. Later stages of the GSVM approach, including its structure and formulation, are shown and explained as well. GSVM's DNA is made up of the values of the kernel parameter and the C parameter. Therefore, GSVM should have two genes, one for each parameter, on its chromosome.

The genetic algorithm starts with a population that all have 15 chromosomes. Continuing along the chromosome, the parameter represents the GRBF Kernel scaling factor, and it is assumed to be positive. When the parameter is used to select a random chromosome, the value of the chromosome's C parameter is sent along to SVM classifiers so that it can be used to make predictions. After that, the classifier accuracy is calculated and confirmed as the chromosome's fitness value.

A. Algorithm

1. Start: Receive results from ITRA.

2. Collect Outputs: Gather outputs from ITRA.

3. Apply Weights to Scores: Integrate with

   $$Weighted\ Score = Output \times Weight. \qquad (1)$$

4. Sum Weighted Scores: Calculate the Sum of Weighted Scores

   $$= \sum i = 1nWeighted\ Scorei. \qquad (2)$$

5. Generate Overall Risk Score:

$$Utilize\ Overall\ Risk\ Score = \ Sum\ of\ Weighted\ Scores/Total\ Weight. \qquad (3)$$

6. Set Risk Thresholds: Establish thresholds for risk levels.

7. Assess Severity: Evaluate the severity of identified risks.

8. Classify Risk Level:

   $$\begin{aligned} &Apply\ Risk\ Level = Low\ if\ Overall\ Risk\ Score < Threshold1, \\ &\qquad Medium\ if\ Threshold1 \leq Overall\ Risk\ Score < Threshold2, \\ &High\ if\ Overall\ Risk\ Score \geq Threshold2., \end{aligned} \qquad (4)$$

9. Dynamic Risk Adjustment: Adapt thresholds based on context.

10. Feedback Loop: Integrate user feedback for continuous improvement.

11. Optimize Mitigation Strategies: Apply machine learning optimization techniques.

12. End: Conclude the Risk Scoring Algorithm process.

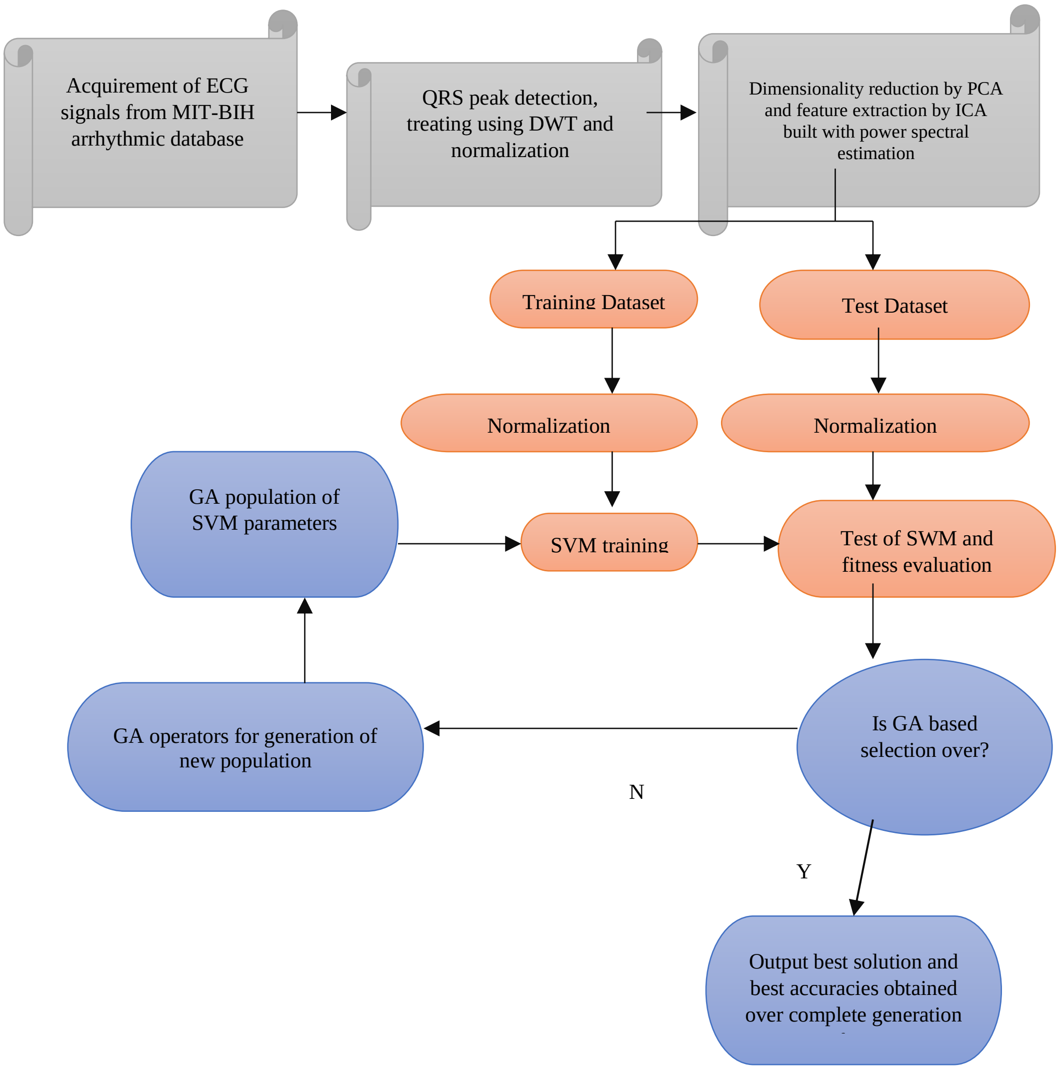

Figure 3: ECG beat classification by using the GSVM algorithm.

As was seen in the preceding section, the accuracy of classification in the SVM model is highly sensitive to the values of the free parameters C and. However, at this moment, it is unknown which parameters should be set to their optimal levels. To find the optimal settings for the SVM, PSO will be used to guide the search. With enough adaptive computations and iterations, PSO can eventually find the best answer. The PSVM technique shown in Figure 4 was applied to the ECG beat classification problem. In the first stage, preprocessing is executed, and the methods for denoising, detecting QRS peaks with DWT, normalizing the data, performing dimensionality reduction with PCA, and extracting features with ICA are all explained. Next, the future steps of the PSVM strategy, including its structure and formulation, are laid forth.

B. Adaptive Threat Intelligence (ATI) ALgorithm

1. Receive cumulative score from BBA.

   BBACcumulative=cumulative score from BBA (5)

2. Real-time and historical threat data collected.

   Rreal_time=real-time threat data
   Hhistorical=historical threat data
   Ttime=current time (6)

3. Threat intensity is dynamically calculated.

$I_{intensity} = \alpha \cdot R_{real\_time} + (1 - \alpha) \cdot H_{historical}$

α is a weighting factor. (7)

4. Probability of threat occurrence estimated.

   $P_{threat} = 1 + e - \beta \cdot (I_{intensity} - \theta) 1$

   β and θ are parameters. (8)

5. If probability exceeds the threshold, an alert is triggered.
   A_{alert}=trigger alert(P_{threat})
   $R_{response}$=response function(A_{alert}, $C_{cumulative}$) (9)

6. If below the threshold, normal operation.

   N_{normal}=normal operation($1 - P_{threat}$)

   $R_{response\_normal}$=response function(N_{normal}, $C_{cumulative}$) (10)

7. Adaptive security measures adjusted.

   $S_{security}$=adaptive security adjustment($R_{response}$, T_{time}) (11)

8. Threat intelligence updated

   U_{update}=update threat intelligence(R_{real_time},$H_{historical}$,T_{time}) (12)

9. Ongoing monitoring and adaptation.

   $M_{monitor}$=ongoing monitoring($S_{security}$, U_{update}) (13)

10. End

The algorithm depicts ATI, dynamically adapting security measures based on evolving threat intelligence. Real-time and historical data are combined to calculate threat intensity and estimate the probability of threat occurrence. Adaptive security adjustments and ongoing monitoring enhance robustness.

The PSVM kernel parameter and the C parameter both have values for a single particle. In light of this, PSVM requires a two-part particle, one for each independent variable. Twenty particles make up the PSO's swarm in the pilot phase. The C parameter value, represented by the particle's leading edge, is typically thought of as an integer between 1 and 10,000,000. The last part of the particle represents the positive number, which is the GRBF kernel scaling factor parameter.

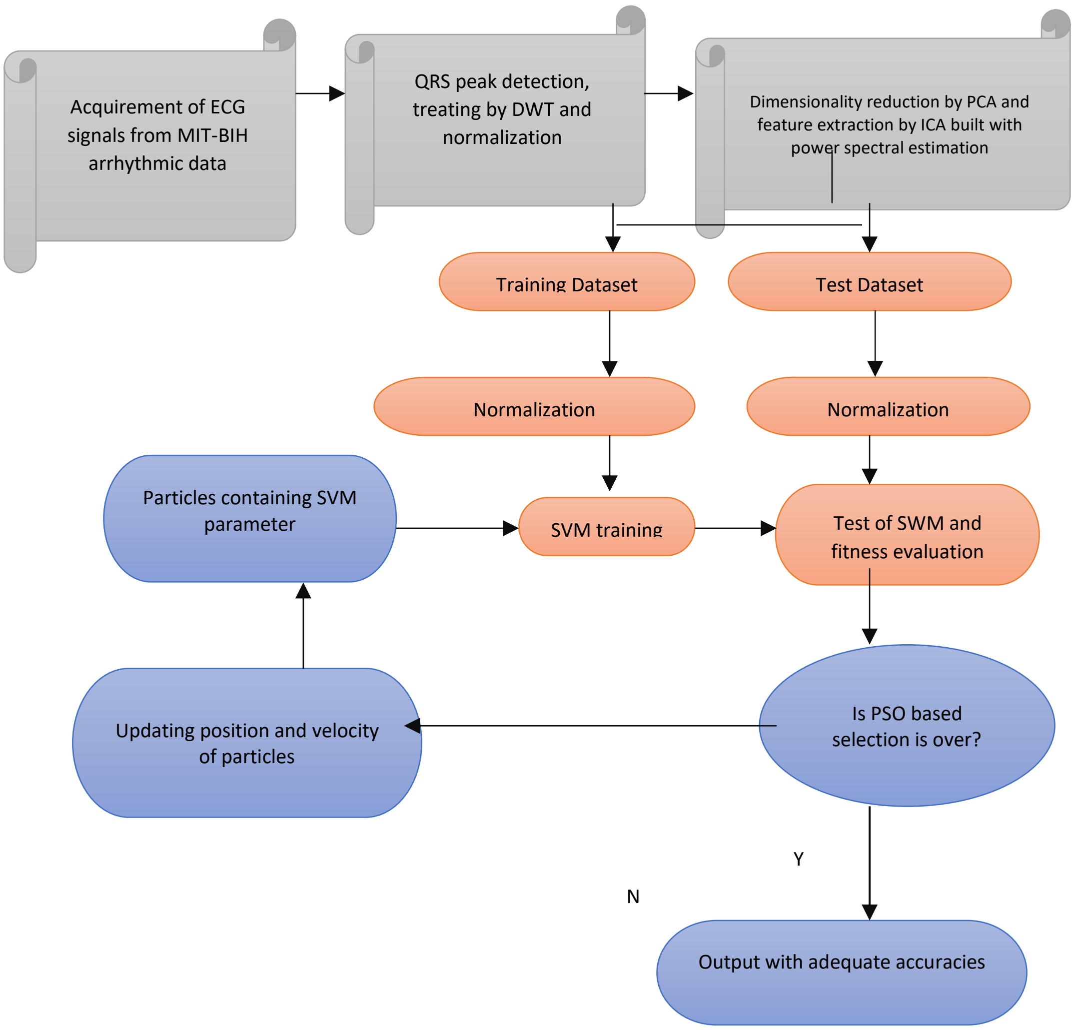

Figure 4: ECG Beat Classification based on PSVM.

When a particle is chosen at random, it carries with it a specific value for the parameter and a specific value for the C parameter; these values are used during the training and testing of SVM classifiers to determine whether or not the particle should be accepted.

8. Result and Discussion

When the ECG signal component for testing is acquired, the classifier uses the maximum peak value of an individual beat to determine which ECG beats to label as belonging to specific cardiac rhythms. Accuracy, Sensitivity, Specificity, and Positive Predictivity are calculated to compare the performance of GSVM and PSVM algorithms. These parameters are defined below.

A. Accurateness

It is a standard method for allocating numerical values to the outcomes of tests. An improved level of accuracy denotes a system that operates more effectively.

$$\text{Accurateness} = \frac{TN+TP}{Total\ data\ Sample}\ X100 \qquad (12)$$

B. Specificity

The absence of inappropriate data classification was the defining characteristic of specificity. Another name for it is the True Negative Rate, which is abbreviated as TNR. The recall of the currently employed method is shown in contrast to other ways that are typically used in Figure 5.

$$\text{Specificity} = \frac{TN}{TN+FP}\ X100 \qquad (13)$$

C. Sensitivity

The sensitivity of the current technique can be conceptualized as the degree to which the model correctly categorizes the test data inside one of its categories. The question that was attempted to be answered by it was, "How many true positives were successfully detected?" There is also a term for it called True Positive Rate.

$$Senstivity = \frac{TP}{TP+FN} X100 \qquad (14)$$

D. Positive Predictivity

The positive predictivity is defined as

$$Positive\ Predictivity = \frac{TP}{TP+FP} X100 \qquad (15)$$

Where TP, FN, FP, and TN stand for True Positive, False Negative, False Positive, and True Negative, respectively. TP refers to the actual number of detected occurrences. For events that were incorrectly denied, use FN. The former, FP, refers to incorrectly discovered events, whereas the latter, TN, refers to appropriately rejected events.

Table 1: Performance Comparison of GSVM and PSVM.

S. No.	ECG Rhythm	Sensitivity		Specificity	
		GSVM	PSVM	GSVM	PSVM
1	NSR	94.21	94.68	98.83	98.78
2	VT	98.89	99.08	99.65	99.38
3	IVR	98.95	98.97	99.56	99.67
4	SBR	89.85	88.14	97.72	97.46
5	AFIB	95.63	94.91	99.69	99.75
6	VF	95.12	95.15	96.58	96.67

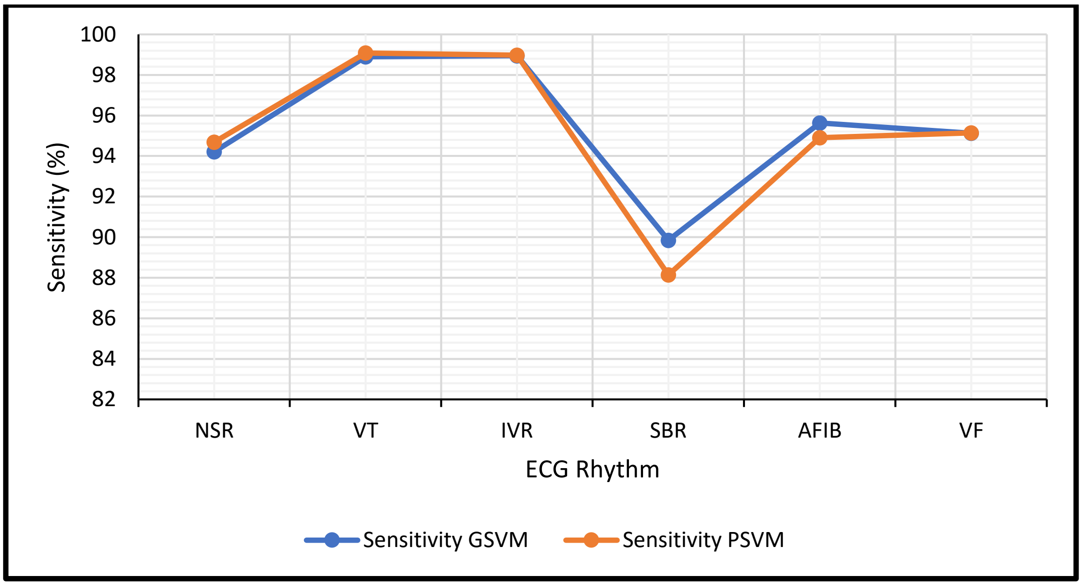

Figure 5: Sensitivity Comparison of GSVM to PSVM.

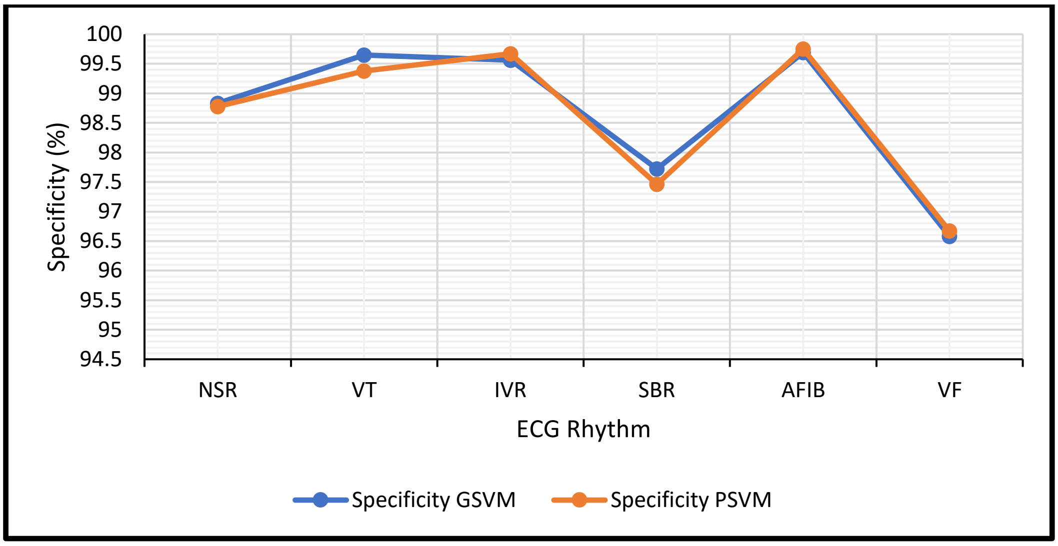

Figure 6: Specificity Comparison of GSVM to PSVM.

Table 2: The Performance Comparison of GSVM to PSVM.

S. No.	ECG Rhythm	Positive Predictivity	
		GSVM	PSVM
1	NSR	98.65	98.40
2	VT	97.75	97.29
3	IVR	98.67	98.72
4	SBR	64.79	71.35
5	AFIB	96.81	97.59
6	VF	80.48	80.42

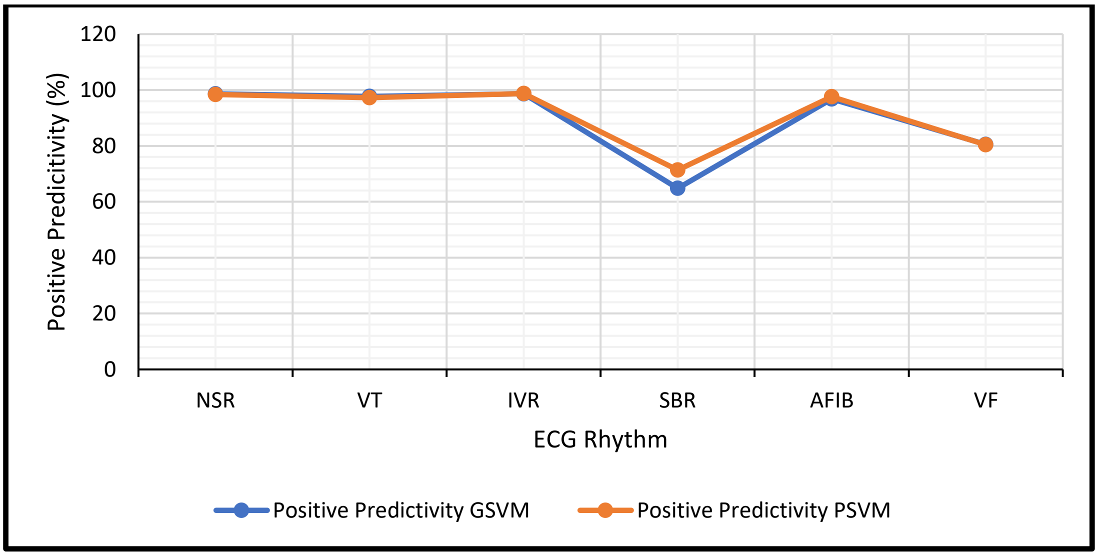

Figure 7: Positive Predictivity Comparison of GSVM to PSVM.

The GSVM method has a best-case classification accuracy of 96.73 percent when used to categorize ECG beats using randomly selected parameters. For PSVM, however, that percentage rises to 96.86%. These findings advocate for the PSVM strategy as the best and most efficient method for the task of classifying ECG rhythmic beats.

From Figures 5, 6 and 7 we can conclude, how well a classifier can identify rhythmic beats without missing any of them is a function of its sensitivity. Because of their similarity in spectral estimates, timing features have played a crucial role in differentiating them; without them, the 2 classes are less sensitive to noise. As a result, most other types of rhythmic beats are misunderstood to be Sinus Bradycardia beats.

The MATLAB software suite was used to calculate the experimental data. There are six groups within the MIT-BIH arrhythmia database. Normal sinus rhythm (NSR), sinus bradycardia (SBR), atrial fibrillation (AFIB), ventricular tachycardia (VT), idiopathic ventricular tachycardia (IVR), and ventricular flutter (VFL) are the several types of abnormal sinus rhythms. The MIT-BIH database is broken down into the aforementioned categories, with each file including a minute-long recording. As was previously indicated, the classifier incorporates an ICA constructed with PSD features. When comparing methods, the PSVM is also simulated to keep computational costs and times low. Results from the aforementioned trials show that Particle Swarm Optimization is superior to other methods in classifying ECG beats. Some of Particle Swarm Optimization's benefits over widely used alternatives are listed below. The very foundation of PSO is an intelligent design.

6. Conclusion

The analysis of heart diseases relies heavily on the automated detection of ECG waves. Most researchers rely on positive illness to determine whether or not an automatic ECG reading device has performed adequately. The precise and dependable detection of the QRS complex, in addition to the T and P waves, is essential to the success of this endeavour. Genetic Algorithm-Support Vector Machine (GSVM) and Particle Swarm Optimization-Support Vector Machine (PSVM) are two methods that are compared and contrasted in this study to examine the classifier for cardiac arrhythmias. The purpose of this work is to better understand how to diagnose and treat cardiac arrhythmias. To find the optimal settings for the SVM, we first use a genetic algorithm (GA) and a particle swarm optimization (PSO) to process the ICA features constructed using the non-parametric power spectral estimation. The research on the origins of GA and PSO is complete. GSVM and PSVM simulation results have been compared and contrasted. Detailed performance data, including Sensitivity, Specificity, Positive Predictivity, and Accuracy percentages, as well as comparisons to the top classifier, have been evaluated and debated. The result suggests that PSVM outperforms GSVM concerning improved accuracy, Sensitivity, Specificity and Positive predictivity.

Funding:

Conflicts of Interest:

References

[1] [1]. Afkhami, RG, Azarnia, G & TinatiMd, A 2016, “Cardiac Arrhythmia Classification UsingStatistical and Mixture Modeling Features of ECG Signals”, Pattern Recognition Letters, vol. 70, pp. 45-51.

[2] Huang, G, Huang, GB, Song, S &You, K 2015, “Trends in extreme learning machines: A review”, Neural Networks, vol. 61, pp. 32–48.

[3] Ingole, MD, Alaspure, SV & Ingole, DT 2014, “Electrocardiogram (ECG) Signals Feature Extraction and Classification using Various Signal Analysis Techniques”, International Journal of Engineering Sciences & Research Technology, vol. 3, issue 1, pp. 39-44.

[4] Kishore, N & Singh, S 2015, “Cardiac Analysis and Classification of ECG Signal using GA and NN”, International Journal of Computer Applications, vol. 127, issue 12, pp. 23-27.

[5] Sharma, A & Bhardwaj, K 2015, “Identification Of Normal And Abnormal ECG Using Neural Network”, International Journal of Information Research and Review, vol. 2, issue. 05, pp. 695-700.

[6] Verma Atul Kumar, Sainu Indu & Saini Barjinder Singh 2018, “Alexander fractional differential window filter for ECG denoising”, Australasian Physical and Engineering Sciences in Medicine vol. 41, pp. 519-539, DOI: 10.1007/s 13246-018-0642-y.

[7] Ramkumar, M & Ganesh Babu, C 2018, “Experimental Analysis for Electrocardiogram Disease Diagnosis with Bio Sensor using Particle Swarm Optimization- Support Vector Machine Classifier”, Sensor Letters (American Scientific Publishers), vol. 16, no. 10, pp. 745-755. Impact Factor: 0.314.

[8] Hassan M.F.u., Lai D., Bu, Y., “Characterization of single lead continuous ECG recording with various dry electrodes”, In Proceedings of the 2019 3rd International Conference on Computational Biology and Bioinformatics, Nagoya, Japan, 17–19 October 2019; pp. 76–79.

[9] Scrugli M.A., Loi D., Raffo L., Meloni P, "A runtime-adaptive cognitive IoT node for healthcare monitoring" In Proceedings of the 16th ACM International Conference on Computing Frontiers, Alghero, Italy, 30 April–2 May 2019; pp. 350–357.
[10] Antoni L., Bruoth E., Bugata P., Bugata Jr P., Gajdoš D., Horvát Š., Hudák D., Kmečová V., Staňa R., Staňková M., et al. "Automatic ECG classification and label quality in training data" Physiol. Meas. 2022, 43, 064008.
[11] Saini S.K., Gupta R, "Artificial intelligence methods for analysis of electrocardiogram signals for cardiac abnormalities: State-of-the-art and future challenges", Artif. Intell. Rev. 2022, 55, 1519–1565.
[12] Hu R., Chen J., Zhou L., "A transformer-based deep neural network for arrhythmia detection using continuous ECG signals", Comput. Biol. Med. 2022, 144, 105325.
[13] Chen J., Liao K., Wei K., Ying H., Chen D.Z., Wu J., "ME-GAN: Learning panoptic electrocardiogram representations for multi-view ECG synthesis conditioned on heart diseases" In Proceedings of the International Conference on Machine Learning, Guangzhou, China, 18–21 February 2022; pp. 3360–3370
[14] Husain K., Zahid M.S.M., Hassan S.U., Hasbullah S., Mandala S., "Advances of ECG Sensors from Hardware, Software and Format Interoperability Perspectives", Electronics 2021, 10, 105.
[15] Acharya U.R., Oh S.L., Hagiwara Y., Tan J.H., Adam M., Gertych A., San Tan R, "A deep convolutional neural network model to classify heartbeats" Comput. Biol. Med. 2017, 89, 389–396.
[16] Hassan S.U., Zahid M.S.M., Abdullah T.A.A., Husain K, "Classification of cardiac arrhythmia using a convolutional neural network and bi-directional long short-term memory", Digit. Health 2022, 8, 1–13.
[17] Schläpfer J., Wellens H.J, "Computer-Interpreted Electrocardiograms: Benefits and Limitations" J. Am. Coll. Cardiol. 2017, 70, 1183–1192.
[18] Al-Hiyali M.I., Yahya N., Faye I., Khan Z., Alsaih K, "Classification of BOLD FMRI signals using wavelet transform and transfer learning for detection of autism spectrum disorder" In Proceedings of the 2020 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES), Langkawi Island, Malaysia, 1–3 March 2021; pp. 94–98.
[19] Hassan S.U.; Zahid M.S.M., Husain K, "Performance comparison of CNN and LSTM algorithms for arrhythmia classification" In Proceedings of the 2020 International Conference on Computational Intelligence (ICCI), Bandar Seri Iskandar, Malaysia, 8–9 October 2020; pp. 223–228.
[20] Zhou S., Tian B., "Electrocardiogram soft computing using hybrid deep learning CNN-ELM" Appl. Soft Comput. 2020, 86, 105778.
[21] Hu H., Zhang Z., Xie Z., Lin S, "Local relation networks for image recognition" In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), Seoul, Korea, 27 October–2 November 2019; pp. 3464–3473.
[22] Gite S., Mishra A., Kotecha K, "Enhanced lung image segmentation using deep learning" Neural Comput. Appl. 2022, 1–15.
[23] Liu X., Wang H., Li Z., Qin L, "Deep learning in ECG diagnosis: A review" Knowl.-Based Syst. 2021, 227, 107187.
[24] Clifford G.D., Liu C., Moody B., Li-wei H.L., Silva I., Li Q., Johnson A., Mark R.G., "A classification from a short single lead ECG recording" The PhysioNet/Computing in cardiology challenge 2017. In Proceedings of the 2017 Computing in Cardiology (CinC), Rennes, France, 24–27 September 2017; pp. 1–4.
[25] Kumari L., Sai Y., "Classification of ECG beats using optimized decision tree and adaptive boosted optimized decision tree" Signal Image Video Process. 2022, 16, 695–703.
[26] Ahmad Z., Tabassum A., Guan L., Khan N.M, "ECG heartbeat classification using multimodal fusion" IEEE Access 2021, 9, 100615–100626.