

MULTICLASS ARRHYTHMIA CLASSIFICATION BASED ON SUPPORT VECTOR MACHINE OPTIMIZED BY GRASSHOPPER OPTIMIZATION ALGORITHM

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Abstract

Grasshopper Optimization Algorithm (GOA) proposed as an optimized classification model for automated arrhythmia identification that uses the support vector machines (SVMs), the DWT technique is used to discover the relevant features that include wavelet decomposition. These multi-domain features are classified with an efficient SVM; various parameters were retrieved and used as features in the training of the SVM with radial basis function (RBF) kernel (SVM-RBF) classifiers. Work carried on MIT-BIH arrhythmia database used for ECG signal classification. Grasshopper Optimization Algorithm used to optimize support vector machine called as GOA-SVM. As seen by the results of the experiments, the proposed algorithm can correctly identify arrhythmias. An impressive 97.90% classification accuracy was achieved using GOA-SVM; the GOA-SVM strategy achieved greater classification accuracy over the Simple SVM approaches.

Keywords: Grasshopper Optimization Algorithm (GOA), Radial basis function, DWT, SVM, Arrhythmia.

1. Introduction

Presently Cardiovascular disease is one of the many ailments that take the lives of countless people each year. Features of heartbeats are exploited for this purpose to help preserve the lives of the patients. One type of physiological signal produced by electrical activity in the heart [Zuo. W. M *et al.* (2008)] is its regular beat, called a heartbeat. The ECG is produced by changes in Bioelectric Potential with relation to time, much like a human heartbeat. Arrhythmia can be diagnosed with the help of ECG signals. It is an arrhythmia where the heartbeat pattern is abnormal. The two most common types are bradycardia and tachycardia, categorized by their BPM (beats per minute). Bradycardia produces drowsiness and occasionally cardiac arrest, whereas tachycardia impairs the heart's capacity to pump blood and results in symptoms such as chest tightness, wheezing, and difficulty breathing, as well as the possibility of a heart attack. Another essential aspect of automated ECG monitoring and classification research is feature extraction and classification diagnosis. Obtaining the ECG signal characteristics with precision and efficiency ensures the accuracy of the arrhythmia diagnosis outcomes.

Numerous studies have examined how cardiac arrhythmias may be classified based on electrocardiographic data. Features, classifiers, and assessment techniques are the most common differences across these approaches. Waveform morphology and transformation-based approaches are now the most widely utilized methods for extracting features from ECG data. It has been common practice in recent decades to use automated ECG classification to help cardiologists identify from ECG recordings. Methods for extracting features from ECG signal that differentiate between heartbeats have included the following: shape of wave functions [De Chazal .P

et al. (2006), De Chazal .P *et al.* (2013) & Ye. C. Kumar. *et al.* (2012)], wavelet based features [Ince, T. *et al.* (2009), X., Zhang *et al.* (2006)], frequency-based features [Senhadji, L. *et al.* (1995)], ECG morphology [Hu, Y. H *et al.* (1997)], The scalability failing to manage huge intra-class fluctuations in the robustness of many existing ECG classification systems remains a significant limitation of ECG classification algorithms. Because they rely so heavily on the supervised training dataset, the methods described above struggle to deal with many unlabeled ECGs. Complex characteristics extracted from transform domains paired with dimensionality reduction technologies considerably increase the computing complexity of the operation. For example, wearable health monitoring devices or mobile applications cannot benefit from feature-extraction frameworks that need a lot of processing power. When it comes to the ECG signals of different patients, the classifier algorithms have failed to perform effectively in practice. Several arrhythmia detection and classification techniques have been proposed in the literature. Authors [Jian. Liu *et al.* (2019)] several approaches for classifying ECG beats are discussed here, including convolution neural networks and improved algorithms. Class N and Class V are well-suited to all of these strategies. The classification accuracy of the CNN model and SVM classifier is up to 91.29% in this technique. [Sahoo. S. *et al.* (2020)] in this review article, many approaches for detecting R-peaks, QRS complexes, and identifying cardiac arrhythmias in ECG data, as well as their classification explained. Methods employing computer-aided diagnostic systems using machine learning and deep learning that are both semi- and fully automated have been demonstrated. When employing morphological and time-frequency based characteristics, the conventional classifiers such as neural network and SVM were more than 99 percent accurate in detecting arrhythmias. [Malik.G.k. *et al.* (2021)] Multi-kernel SVM is used to classify different arrhythmias in this study. Peak finder algorithm and higher-order statistics are used to extract 15 different features, resulting in a data set for 30 distinct signals (from the MIT BIH database). Different kernel SVMs uses data sets of features to classify the signals. Increasing the number of classes in datasets and adding more kernels to handle datasets more quickly and efficiently would help us discover arrhythmias in computer-aided diagnostics more quickly and efficiently. [Rahul. Jagdeep *et al.* (2021)] this study provides a better technique for identifying cardiac arrhythmias based on the RR interval. The RR interval was the first of nine characteristics retrieved from the beat segments. In order to arrive at the findings, methodology used the extracted features dataset and five classifiers (kNN, SVM, DT, NB and RF). In order to develop and validate algorithm MIT-BIH database used. The classifiers were tested using a 10-cross-fold validation approach, they are better than any other methods employed in this procedure, including SVM and Random Forest. According to the results, PAC and PVC beats can be automatically classified using the suggested approach.

This paper proposed a method using the GOA-SVM (grasshopper-optimized support vector machine) technique for the identification of different arrhythmias. The optimization algorithm classified the arrhythmias by optimal parameters for SVMs. The SVM kernel parameters are tuned, and then an arrhythmia classification model is built. GOA-SVM is the acronym for this hybrid approach. In the experimentation, five distinct datasets beats are used for comparisons with simple SVM classification method: Results show that the GOA-SVMs classification system has a significant advantage in terms of classification accuracy when compared to the standard SVMs classification method and various literature articles that have been used in the past.

2. Database

The MIT BIH arrhythmia database [Moody, G. B *et al.* (2001)] provided the physiological ECG signal for this study. There are 48 half-hour ECG recordings in the MIT BIH arrhythmias database. A sampling frequency of 360 Hz is used to sample the signals. Each signal in the database has its own annotated file, which contains information about the signal's beat, rhythm, and other aspects. Researchers use this database to test their arrhythmia detection and classification methods. The current study used 32 full-length recordings to identify data as five different classes, with abnormal values indicating an arrhythmia-related ECG signal; the original labeling of the database includes 16 classes of rhythms but Advancement of Medical Instrumentation (AAMI) representation of cardiac arrhythmia in five different classes. As shown in Table 1.

Classes	Description	Total Beats
N	Beats Originating in the sinus Node	89665
S	Supraventricular ectopic beats	2940
V	Ventricular ectopic beats	7478
F	fusion beats	802
Q	Unclassified beats	17

TABLE 1, MIT-BIH Database (AAMI Division)

3. Methodology

This section explains the research methodology used in this work. An ECG signal beats of five types are used from the MIT BIH database, Preprocessing, feature extraction, classification and optimization diagnosis are four main components of automated arrhythmia's classification system

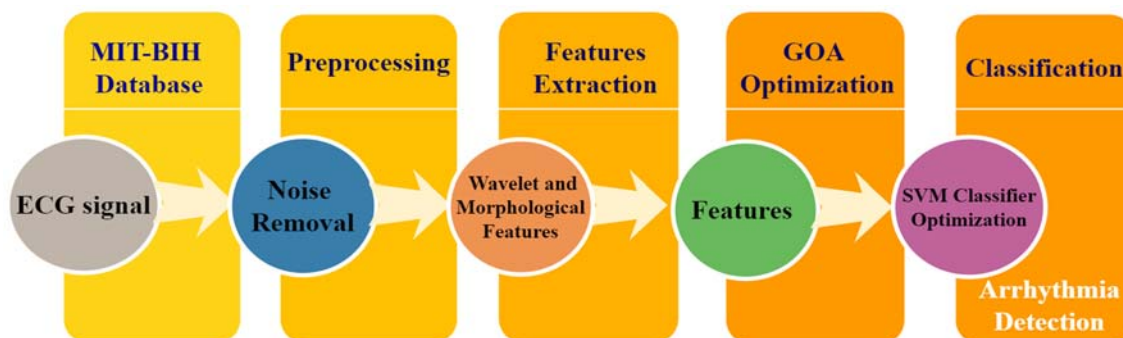


Fig 1. Steps of proposed automatic arrhythmia classification system

The suggested processing method's block diagram is shown in Fig. 1. The first step is to select ECG data sets for the research work; the proposed methodology uses MIT-BIH data sets. The second step is a crucial step to perform signal noise removal. Signals in the database contain redundant and noisy data; researcher performs signal noise removal by examining the data. The following third step is extracting the attributes of the preprocessed signals using techniques such as wavelet packet decomposition and slope threshold methods, The wavelet transform [Mar, T. *et al.* (2011)], [Al-Fahoum, *et al.* (1999)] extract the ECG data is by elevating and enhancing the semi-soft de-noising approach, The recommended technique described in step 4 may be used to make the feature vector data sets. In order to identify arrhythmia the two different kinds of features extracted, the DWT computation and morphological feature extraction should be taken into consideration. For arrhythmias diagnosis, the Grasshopper optimization algorithms suggest best characteristics of SVM kernel. Finally, the SVM is tuned using the GOA method. Their tuning parameters strongly influence the classification accuracy of SVM. Poor classification results are caused by parameter settings that are not correct. SVM's radial basis kernel function has parameters that need to be tuned.

3.1. Pre-processing

Preprocessing is used to eliminate signal interferences from various physiological signals, all of which are weak by nature and intermingled with various types of interferences. To provide the highest level of precision ECG signal must be free of interference. Otherwise, incorrect clinical care results from categorization errors. Low-frequency interferences, baseline drift, power line interferences [Kumar, Y *et al.* (2010)], and high-frequency interferences are the four forms of interference. In order to eliminate these unwanted sounds, Database is band-pass filtered at the frequency range from 0.01 to 100 Hz and digitized at 360 samples per second. Using two steps of median filtering [Awodeyi, A. E *et al.* (2013)], Different kind of noise eliminated from these signals.

3.2. Feature extraction

Using support vector machines to classify arrhythmia, an input vector must be generated, which should comprise the ECG signal's morphology and rhythm characteristic, as illustrated in Fig. 3. In order to detect arrhythmia's, the Feature Extraction phase is critical. Features are extracted in order to provide a collection of extracted parameters of ECG signal. This is the goal of this stage. In order to accurately classify arrhythmias, the selection criteria for these characteristic parameters must be carefully considered. Both morphological [De Chazal, P *et al.* (2004), & Lin, C. C *et al.* (2014)] and wavelet features, shown in Fig 3, are included in the input vector used to train the classifier in this study. Different waveform (PQRST) and interval features were extracted to use the morphological peculiarities of various heart rhythms. Interval properties such as RR PQ can store essential information regarding heart rhythms and have been utilized by numerous research studies [De Chazal, *et al.* (2004) & Lin, C. C (2014)] It is a novel feature extraction method that uses discrete wavelet transform (DWT). Signals decompose into simple building components that are well-localized in time and frequency. Research on ECGs and other physiological signals, such as heart rate variability (HRV), have significantly benefited from their usage in signal processing. DWT in the Fourier transform, spectral information is the primary emphasis. The real benefit of the Wavelet transform over the Fourier transform is that it captures both temporal and spectral information. As with the Discrete Fourier Transform, the Discrete Wavelet Transform (DWT) may be done numerically using discretely sampled wavelets (DFT). DWT is defined, for example, as follows for the signal $x(t)$.

$$DWT(m; n) = \frac{1}{\sqrt{2^m}} \int_{-\infty}^{\infty} x(t) \psi\left(\frac{t-2^m n}{2^m}\right) dt \quad (1)$$

In DWT, m is the decomposition level and n is the shifting parameter, reflecting the DWT decomposition algorithm. Passing the signal through low and high pass filters results in $x(n)$ DWT. The detail and approximation coefficients are defined as the outputs of the high pass and low pass filters, respectively. These two filters have cutoff frequencies in the centre of the input signal's maximum frequency range. As a result, the filter retains half of the original signal's frequencies. According to the Nyquist rule, just half of the samples should be retained in this situation. The filters' output signals are down-sampled to accomplish this result. As a result, the first stage of breakdown has been completed. Approximation coefficients are the only ones that need to be decomposed in the following phase, use filters to further decompose the approximation coefficients before going back to down-sampling. With DWT, the output frequency resolution is doubled for each level of decomposition, Because only half of the frequencies in the input signal are left after decomposition, the frequency resolution of the output signal is doubled when using DWT. On the other hand, Down-sampling reduces the original signal's temporal resolution. The multi-level breakdown process will continue indefinitely. DWT with third-level decomposition, for example, is depicted. Details and approximation coefficients are separated from one other in wavelet decomposition. The number of samples in the original signal must be a multiple of 2^m , where m is the decomposition level. Decomposition of the 64-sample signal with the maximum frequency f_m yields the frequencies and samples at the fourth level.

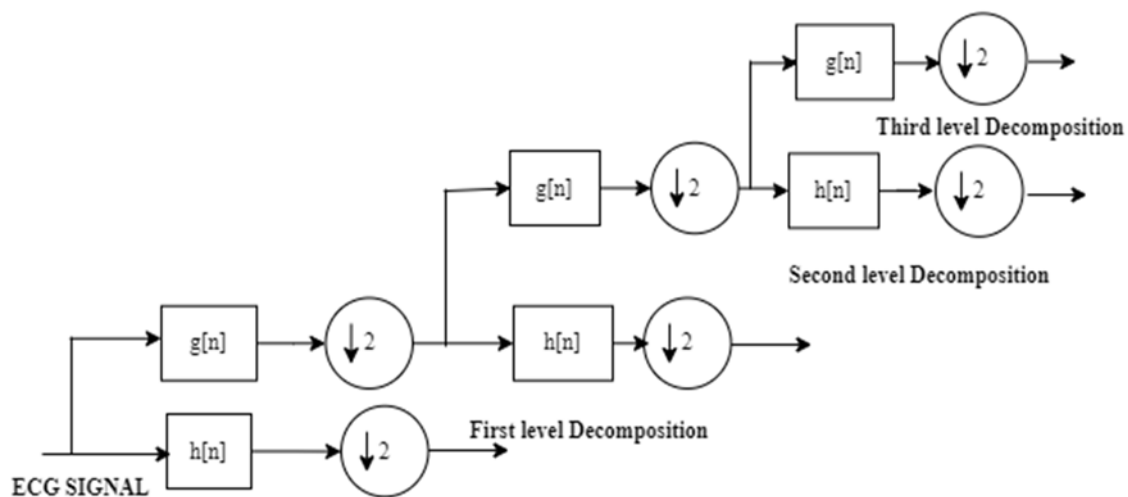


Fig 2: DWT Decomposition for features extraction

A total of 21 features, including morphological and wavelet features, such as the R-R, P-Q, P-R, and P-T intervals, have the location of wave (P, Q, R, S, T) with amplitude of each ECG signal in the analysis process. As a result of this manual process, each ECG beat has been extracted and saved as an individual vector. The tag of each vector has been made with labels like N (Beats originating in the sinus node), S (supraventricular ectopic beats), V (ventricular ectopic beats), F (fusion beats) and Q (unclassified beats), respectively. These tags may be used in Performance evaluation to identify the various types of arrhythmias.

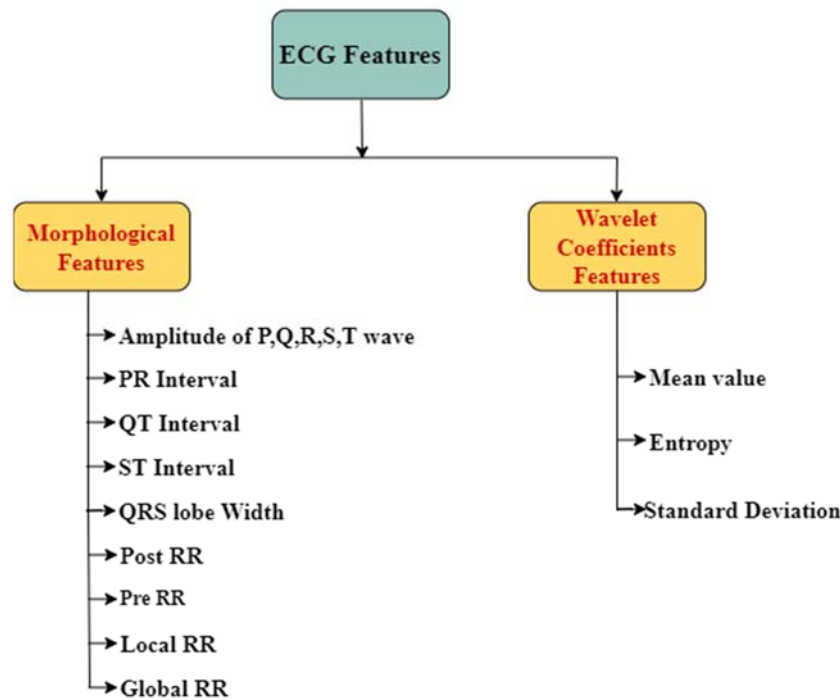


Fig 3: Features used in study

3.3. Classification

In this part the classification is done using the SVM [Cortes, C., & Vapnik, V. (1995)]. After separating the data into train and test sets and extracting features for both classes, train and test sets were split into two separate datasets. Data from the training set is used to calculate test set proportions, whereas data from the latter is used for testing purposes alone. The SVM classifier used RBF kernel [Zhang, N., Ruan, *et al.* (2009)] to categories the retrieved feature from the ECG data. Finally the primary goal of this classification method, it aims to maximize class margins and minimize hyper-plane focuses. For the purposes of this classifier, each of these qualities may necessitate a different concept of resemblance (an alternate portion). Because the bit contains a non-straight change, it is unnecessary to assume that the change is of a utilitarian sort that allows information to be separated from its context. The kernel functions of the SVM classification are used to begin the non-linear process. The classification procedure in this work makes use of the radial bias function (RBF) kernels [Kim, J *et al.* (2009)].

$$RBFk = \exp(-||x - y||^2/2\sigma^2) \quad (2)$$

Finally, the kernel variable is used to classify the data using support vectors. SVM parameters may be improved by using an optimization technique. The performance of SVMs is affected by the values of two kinds of parameters: penalty constant C parameters and kernel functions parameters. The highest level of classification accuracy can only be obtained by carefully selecting these parameters. Unique GOA-SVM hybrid classification system parameters are presented in this study as a result. The GOA approach was used to update the most critical parameters of these kernels to their original values. in this work, two distinct types of features picked and optimized with the help of GOA. Then categorize the data into five categories of arrhythmias

4. Grasshopper optimization algorithm

Proposed Grass Hopper Optimization Algorithm (GOA) methodology is based on Swarm Intelligence ‘S_i’ methodologies. Optimizing algorithms based on Swarm Intelligence are utilized for feature selection. Swarm Intelligence is a technology that uses the observation of clustered particles. Swarm Intelligence is one of the most superior algorithmic designs to improve the features based on the fitness function, which helps in pick better features based on ECG arrhythmia category classification. The algorithm of Grasshopper Optimization (GOA) is explained as; the grasshoppers are regarded as a pest because they harm to crops and farming. Grasshoppers are generally observed alone in the wild, but they form one of the world’s most extensive when they form a swarm. A farmer’s worst fear, the swarm might be the size of a continent. Grasshopper swarms are remarkable in that the swarming activity is present in both the nymph and adult [Rogers, S. M. *et al.* (2003)] of life. Hundreds of millions of nymph grasshoppers leap and scurry about in a cylinder-like motion. These predators devour all vegetation in their route. Adults who continue this activity create a swarm in the sky. They travel long distances in this manner.

Swarms of larval grasshoppers are characterized by their slow, sluggish movement and short, precise steps. However, as adults, the swarm is all about long-range and sudden activity. Grasshoppers' swarming behavior is also characterized by a need to find food. As described in the introduction, nature inspired algorithms split the search process logically into two tendencies: exploration and exploitation. In exploration, the search agents are urged to move quickly, but they prefer to move slowly during exploitation. Fig. 4. depicts artificial grasshoppers engaging in various social activities, all of which boost their attractiveness.

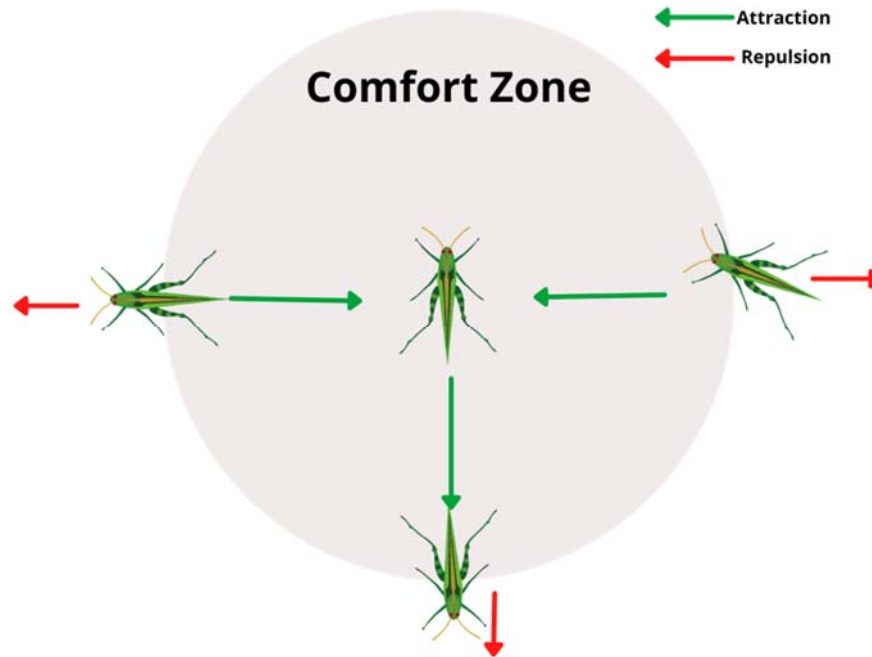


Fig 4: Grasshoppers Interaction

Grasshoppers are not unusual in their ability to do both things interaction and find their prey. An algorithm based on natural phenomena might be developed if this behavior can be mathematically represented [Topaz, C. *et al.* M (2008)]. To arrive at this result, researchers employed the following mathematical formula:

$$Y_i = S_i + G_i + W_i \quad (3)$$

Where Y_i used for i -th grasshopper Position, S_i for social interaction, G_i is the gravity force on the i -th grasshopper, and W_i shows the wind advection. To provide random behavior of grasshopper the equation can be written as: (where R_1, R_2, R_3 Represents Random Numbers.)

$$Y_i = R_1 S_i + R_2 G_i + R_3 W_i \quad (4)$$

The functions in relation to grasshopper social interaction (attraction and repulsion) represent as "Eq. (5)". There is neither attraction nor repulsion when a grasshopper is not near another grasshopper. "Comfort zone" or "comfortable distance" refers to "Eq. (5)". Where d_{ik} is represents the distance between i -th and the k -th grasshopper.

$$S_i = \sum_{k=1, k \neq i}^N S(d_{ik}) \hat{d}_{ik} = \frac{|Y_k - Y_i|}{d_{ik}} \quad (5)$$

$$d_{ik} = |Y_k - Y_i|$$

In order to calculate the social forces function, the following formula is used "Eq. (6)". Where 'a' is the strength of attraction and 'm' is the attractive length scale

$$s(R) = ae^{\frac{-R}{m}} - e^{-r} \quad (6)$$

If 'g' is the gravitational constant and \hat{e}_g shows a unity vector towards the centre of earth than $G_i = -g\hat{e}_g$

$$W_i = u\hat{e}_{wi}$$

Constant drift shown as u and \hat{e}_{wi} is wind directional unity vector (nymph grasshoppers, are strongly dependent on the direction of the wind) Substituting S , G , and W in “Eq. (3)”.

$$Y_i = \sum_{k=1, k \neq i}^{N-y_i} S(|y_k|) \frac{y_k - y_i}{d_{ik}} - g\hat{e}_g + u\hat{e}_{wi} \quad (7)$$

It is difficult to solve optimization issues using “Eq. (7)” since grasshoppers soon reach their comfort zone, and the swarm system does not converge to the desired place. The “Eq. (8)” is an improved version.

$$Y_i^d = c \left(\sum_{k=1, k \neq i}^N c \frac{ub_d - lb_d}{2} S(|Y_d^j - Y_d^i|) \frac{y_k - y_i}{d_{ik}} \right) + \hat{T}_d \quad (8)$$

C must be reduced proportionally with the number of iterations to maintain a good balance between exploration and exploitation as illustrated by “Eq. (9)”. As the number of iterations increases, this process encourages exploitation. C_{max} is the maximum value, C_{min} is the lowest value, l is the current iteration, and L is the maximum number of iterations.

$$c = C_{max} - l \frac{C_{max} - C_{min}}{L} \quad (9)$$

Every time a grasshopper moves, their coordinates are compared to the coordinates of every other grasshopper in the swarm. Through this, GOA is able to avoid being bound in an optimal region. By using “Eq. (9)” it is possible to remove some features while still keeping the data’s discriminating power to improve speed due to features reduction. The classifier may develop a more robust solution and achieve higher generalization performance if relevant features from ECG signals are correctly selected. Both the optimum feature subset and SVM parameters may be generated using GOA. SVM tuning settings have a significant influence on the accuracy of their categorization. The penalty parameter C and the radial basis kernel function parameters σ are among the SVM parameters that require optimization. The optimization process is completed sequentially. In this situation, each stage either keeps the feature set constant or optimizes the SVM parameters. The optimum position is the subset that yields the maximum fitness value. The algorithm’s fitness function is often used to find the optimal solution. The accuracy of each grasshopper (Search Agent) varies. A fitness value is returned to throw search process by averaging all accuracy values over all folds, as shown in the following function

$$f(p, I) = \sum_{k=1}^N \text{acc}_{pkl} / N \quad (10)$$

The grasshopper fitness $f(p, I)$ in iteration I , N represents the number of folds selected for cross validation and acc_{pkl} reflects that accuracy.

5. Proposed GOA-SVM Approach for arrhythmia classification.

SVM classifier accuracy may be improved by automatically calculating the best SVM parameter values, for that GOA-SVM proposed methodology is designed to do just that: The excellent global convergence and flexibility of GOA were fully used to identify the best parameters of SVM using GOA. Because of this, the GOA-SVM technique developed in this research may combine the advantages of GOA and SVM. GOA also dynamically optimizes the SVM kernel parameter values (C , σ) for arrhythmia classification. After that, the best parameters for the SVM-RBF classifier for arrhythmia classification are used for input feature set feed to the classifier as Fig.5. Explains the GOA algorithm’s stages. A variety of metrics, such as classification accuracy and sensitivity and specificity, are used to analyze the information gained from the study.

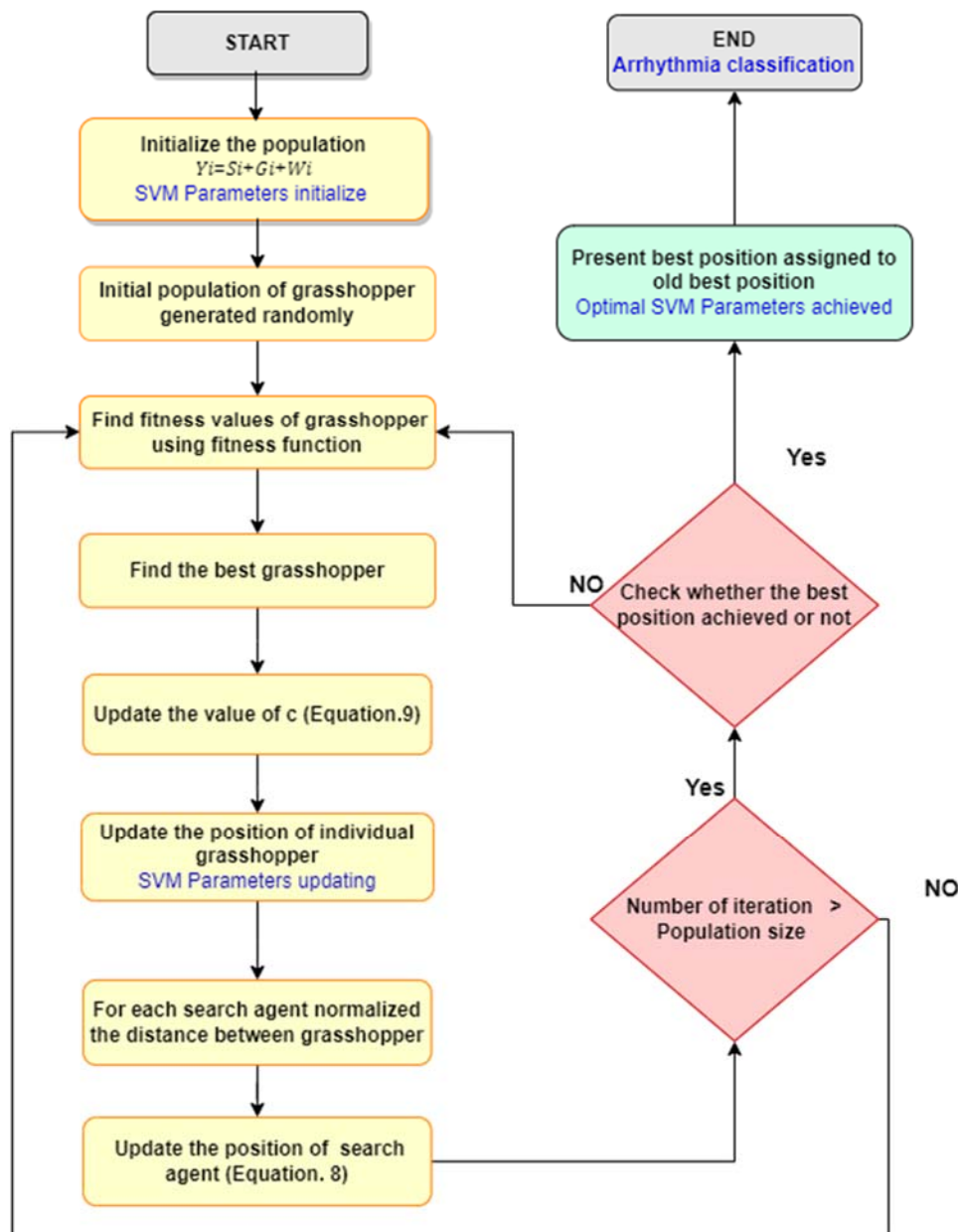


Fig 5: Flow chart of GOA-SVM

6. Results and discussion

In the exploratory MIT-BIH arrhythmia database was used 60% datasets use for training and rest 40% used for classification purpose, which was done in MATLAB (R2015a). ECG signals of 30 minutes utilized in this study, while the testing data set is used to assess the trained classifier's accuracy and performance in identifying ECG arrhythmias. For the current multiclass classifier problem, 21 features are retrieved using the DWT transform and morphological parameters calculation for feature extraction. SVM classifier training and testing vectors use a combination of these characteristics. The proposed GOA-SVM method was tested to see if it could be used to select and optimize SVM parameters. It was calculated by averaging the accuracies of the classification in the experiment. Table.2 shows the classification results achieved by implementing the suggested GOA-SVM versus the classic SVM classification technique for the RBF kernel function. Results show that GOA-SVM has the best performance.

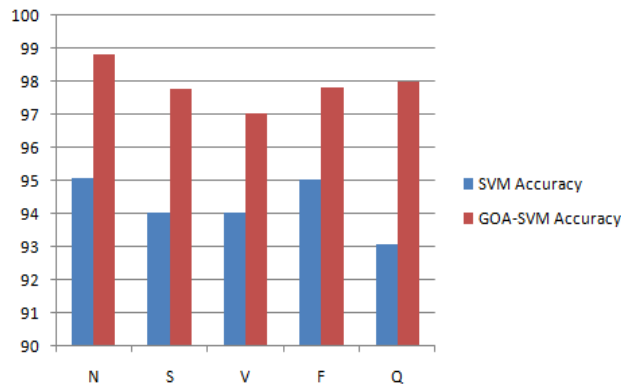


Fig 6: Accuracy Performance analysis

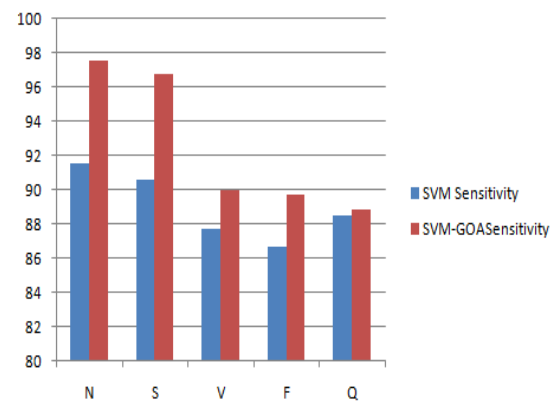


Fig 7: Sensitivity Performance analysis

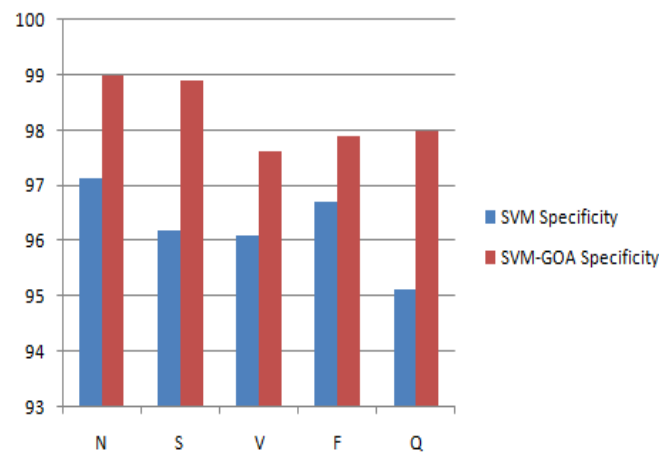


Fig 8: Specificity Performance analysis

Class	SVM			GOA- SVM		
	Acc	Sen	Spec	Acc	Sen	Spec
N	95.08%	91.60%	97.15%	98.81%	97.60%	99.00%
S	94.03%	90.60%	96.20%	97.80%	96.80%	98.90%
V	94.03%	87.70%	96.10%	97.05%	90.00%	97.62%
F	95.04%	86.70%	96.70%	97.84%	89.78%	97.90%
Q	93.09%	88.50%	95.12%	98.00%	88.90%	98.00%
Average	94.25%	89.02%	96.25%	97.9%	92.61%	98.28%

TABLE 2. Performance analysis of different classification approaches

Fig. 6 to 8 show classification results in terms of Accuracy ‘Acc’, Sensitivity ‘Sen’ and Specificity ‘spec’ obtained via applying the proposed GOA-SVM against the traditional SVM classification approach. MIT-BIH databases provided the source data for the proposed ECG signal classification processing approach (Table. 1, for different classes), producing a high accuracy in classifying the signals. 94.25% Acc, 89.02% Sen and 96.25% Spec were attained on an average by the Standard SVM method across five classes. With the GOA-optimized SVM, 97.9% of the Acc, 92.61 % of the Sen, and Spec 98.28 % on an average of five classes were attained. The GOA-SVM for the N class had a higher number of beats than the Q class; hence the classifier was trained with more data for N and less for Q. for the N class, 88598 beats out of 89665 beats were accurately recognized as sinus Node Class, with an average accuracy of 98.8 %. Table 1 and Table 2 provide a straightforward interpretation of the data. The suggested ECG recognition system’s findings were compared to standard SVM classification systems, the comparison results in Table. 2 shows that the classifiers used GOA-SVM is far better than Standard

SVM. The classification accuracy of GOA-SVM used in this paper is higher than SVM based algorithms in other literature as described previously, indicating that the proposed method has higher classification accuracy.

7. Conclusion

In this paper, the proposed method can successfully distinguish between five kinds of arrhythmia based on wavelet characteristics and morphological data features. A technique like GOA- SVM classifier for arrhythmias classification yields better outcomes than previous studies. Five different Arrhythmias beats are now being classified using a new GOA-SVM technique that takes into account the findings of this work. The improved fitness function by GOA achieved high accuracy in the suggested technique. The DWT approach extracts the appropriate features from the ECG data. Experimentation with the MIT-BIH arrhythmia database showed that this method could accurately identify arrhythmias. Arrhythmia identification in ECG by GOA-SVM classifier for the RBF kernel has 97.9 % classification accuracy. GOA-SVM beat the standard SVM (RBF kernel) classification technique.

8. References

- [1] Zuo, W. M., Lu, W. G., Wang, K. Q., & Zhang, H. (2008). Diagnosis of cardiac arrhythmia using kernel difference weighted KNN classifier. *Computers in Cardiology* (pp. 253-256). IEEE.
- [2] De Chazal, P., & Reilly, R. B. (2006). A patient-adapting heartbeat classifier using ECG morphology and heartbeat interval features. *IEEE transactions on biomedical engineering*, 53(12), 2535-2543.
- [3] De Chazal, P. (2013). Detection of supraventricular and ventricular ectopic beats using a single lead ECG. In *2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* (pp. 45-48). IEEE.
- [4] Ye, C., Kumar, B. V., & Coimbra, M. T. (2012). Heartbeat classification using morphological and dynamic features of ECG signals. *IEEE Transactions on Biomedical Engineering*, 59(10), 2930-2941.
- [5] Ince, T., Kiranyaz, S., & Gabbouj, M. (2009). A generic and robust system for automated patient-specific classification of ECG signals. *IEEE Transactions on Biomedical Engineering*, 56(5), 1415-1426.
- [6] Jiang, X., Zhang, L., Zhao, Q., & Albayrak, S. (2006). ECG arrhythmias recognition system based on independent component analysis feature extraction. In *TENCON 2006-2006 IEEE Region 10 Conference* (pp. 1-4). IEEE..
- [7] Senhadji, L., Carrault, G., Bellanger, J. J., & Passariello, G. (1995). Comparing wavelet transforms for recognizing cardiac patterns. *IEEE Engineering in Medicine and Biology Magazine*, 14(2), 167-173.
- [8] Hu, Y. H., Palreddy, S., & Tompkins, W. J. (1997). A patient-adaptable ECG beat classifier using a mixture of experts approach. *IEEE transactions on biomedical engineering*, 44(9), 891-900.
- [9] Liu, J., Song, S., Sun, G., & Fu, Y. (2019). Classification of ECG arrhythmia using CNN, SVM and LDA. In *International Conference on Artificial Intelligence and Security* (pp. 191-201). Springer, Cham.
- [10] Sahoo, S., Dash, M., Behera, S., & Sabut, S. (2020). Machine learning approach to detect cardiac arrhythmias in ECG signals: a survey. *Irbm*, 41(4), 185-194.
- [11] Malik, G. K., Kumar, Y., & Panda, M. (2021). Multi-kernel SVM Approach for Arrhythmias Classification. In *Proceedings of Integrated Intelligence Enable Networks and Computing* (pp. 733-739). Springer, Singapore.
- [12] Rahul, J., Sora, M., Sharma, L. D., & Bohat, V. K. (2021). An improved cardiac arrhythmia classification using an RR interval-based approach. *Biocybernetics and Biomedical Engineering*, 41(2), 656-666.
- [13] Moody, G. B., & Mark, R. G. (2001). The impact of the MIT-BIH arrhythmia database. *IEEE Engineering in Medicine and Biology Magazine*, 20(3), 45-50.
- [14] Mar, T., Zaunseder, S., Martínez, J. P., Llamado, M., & Poll, R. (2011). Optimization of ECG classification by means of feature selection. *IEEE transactions on Biomedical Engineering*, 58(8), 2168-2177.
- [15] Al-Fahoum, A. S., & Howitt, I. (1999). Combined wavelet transformation and radial basis neural networks for classifying life-threatening cardiac arrhythmias. *Medical & biological engineering & computing*, 37(5), 566-573.
- [16] Kumar, Y., & Malik, G. K. (2010). Performance analysis of different filters for power line interface reduction in ECG signal. *International Journal of Computer Applications*, 3(7), 1-6.
- [17] Awodeyi, A. E., Alty, S. R., & Ghavami, M. (2013). Median filter approach for removal of baseline wander in photoplethysmography signals. In *2013 European Modelling Symposium* (pp. 261-264). IEEE.
- [18] De Chazal, P., O'Dwyer, M., & Reilly, R. B. (2004). Automatic classification of heartbeats using ECG morphology and heartbeat interval features. *IEEE transactions on biomedical engineering*, 51(7), 1196-1206.
- [19] Lin, C. C., & Yang, C. M. (2014). Heartbeat classification using normalized RR intervals and morphological features. *Mathematical Problems in Engineering*, 2014.
- [20] Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, 20(3), 273-297.
- [21] Zhang, N., Ruan, S., Lebonvallet, S., Liao, Q., & Zhu, Y. (2009). Multi-kernel SVM based classification for brain tumor segmentation of MRI multi-sequence. In *2009 16th IEEE International Conference on Image Processing (ICIP)* (pp. 3373-3376). IEEE.
- [22] Kim, J., Shin, H. S., Shin, K., & Lee, M. (2009). Robust algorithm for arrhythmia classification in ECG using extreme learning machine. *Biomedical engineering online*, 8(1), 1-12.
- [23] Rogers, S. M., Matheson, T., Despland, E., Dodgson, T., Burrows, M., & Simpson, S. J. (2003). Mechanosensory-induced behavioural gregarization in the desert locust *Schistocerca gregaria*. *Journal of Experimental Biology*, 206(22), 3991-4002.
- [24] Topaz, C. M., Bernoff, A. J., Logan, S., & Toolson, W. (2008). A model for rolling swarms of locusts. *The European Physical Journal Special Topics*, 157(1), 93-109.

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