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Dipper Throated Algorithm for Feature Selection and Classification in Electrocardiogram

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Abstract: Arrhythmia has been classified using a variety of methods. Because of the dynamic nature of electrocardiogram (ECG) data, traditional handcrafted approaches are difficult to execute, making the machine learning (ML) solutions more appealing. Patients with cardiac arrhythmias can benefit from competent monitoring to save their lives. Cardiac arrhythmia classification and prediction have greatly improved in recent years. Arrhythmias are a category of conditions in which the heart's electrical activity is abnormally rapid or sluggish. Every year, it is one of the main reasons of mortality for both men and women, worldwide. For the classification of arrhythmias, this work proposes a novel technique based on optimized feature selection and optimized K-nearest neighbors (KNN) classifier. The proposed method makes advantage of the UCI repository, which has a 279-attribute high-dimensional cardiac arrhythmia dataset. The proposed approach is based on dividing cardiac arrhythmia patients into 16 groups based on the electrocardiography dataset's features. The purpose is to design an efficient intelligent system employing the dipper throated optimization method to categorize cardiac arrhythmia patients. This method of comprehensive arrhythmia classification outperforms earlier methods presented in the literature. The achieved classification accuracy using the proposed approach is 99.8%.

Keywords: Feature selection; electrocardiogram; metaheuristics; dipper throated algorithm

1 Introduction

High fatality and morbidity rates are caused mainly by the heart disease as one of the most common diseases in the world with over 385,000 individuals dying each year. A heart attack happens every 34 s [1,2] in the United States alone. An erratic heartbeat, also known as cardiac arrythmia, is the most noticeable indication of heart disease. The ECG, which records electrical impulses produced by the heart from electrodes put on the body and visually visualizes the patterns of activity, is the most routinely used technique for assessing heart function [3]. P, Q, and QRS complex waves are the primary variables produced by ECG signals. The interval, form, and correlations of P, Q, and QRS complex wave characteristics in heart disease patients may be studied using a variety of basic factors. Any abrupt change in these limitations implies a cardiac condition in which the heartbeat is irregular, either quicker or slower than normal. Arrythmia can be caused by a number of different things [4]. As a result, arrythmia should be identified and treated as quickly as feasible. Arrhythmia is most commonly associated with the start of a cardiac disease such as insufficient blood flow from the heart, shortness of breath, chest discomfort, tiredness, or unconsciousness. An aberrant ECG signal can be seen [5,6]. Both bradycardia and tachycardia are types of arrhythmias. Bradycardia is defined as a heartbeat that is less than 60 beats per minute (bpm), whereas tachycardia is defined as a pulse that is greater than 100 bpm [7]. The need of efficient and precise arrhythmia categorization and detection is becoming clear with the advent of remotely managed healthcare systems for heart disease patients. In the last few years, diagnostic systems based on various machine learning (ML) algorithms have been developed to increase the accuracy of arrhythmia classification from ECG recorded signals, which is a difficult problem [8]. It is difficult to choose appropriate procedures for detecting and classifying cardiac disease. It entails taking into account the setting, data analysis, and the individual requirements of patients [9]. ML methods employ techniques that let a computer to learn from its own experiences rather than having to be explicitly programmed. The goal is to create an algorithm that can take a group of patterns and automatically generalize from them without the need for human intervention. Cluster analysis, or clustering, is an unsupervised ML technique. Clustering is a technique for categorizing observations into different groups depending on how similar the objects in each category are. Several intelligent disease diagnostic systems [10–15] have implemented clustering methods.

Electrocardiogram (ECG) represents the electrical activity of the heart and picked up using electrodes placed around the heart of the patient. ECG signal provides information about heart beats, regularity of heart rhythm, and detection of heart failure along with disorders that affects performance of the heart. A normal ECG signal is showing in Fig. 1.

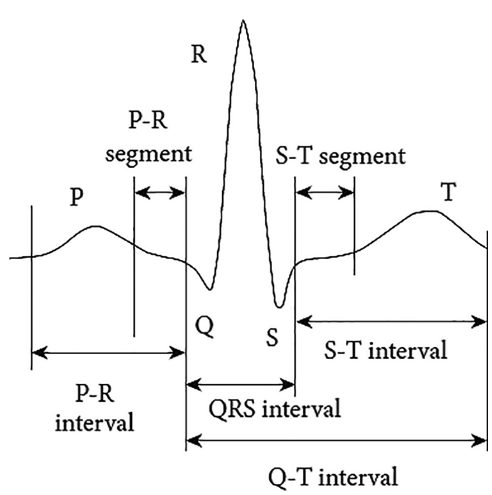

Figure 1: Normal electrocardiogram signal

The normal ECG signal can be divided into three waves (P-QRS, T), two segments (PR, ST), and four intervals (PR, QRS, ST, QT). P wave represents the contraction of the atria it's amplitude lies between (0.2–0.25 mV) while it's duration lies between (0.06–0.12 s). The QRS complex marks the start of the contraction of the ventricles, it's amplitude between (0.5–3 mV) and duration between (0.06–0.1 s). The T wave corresponding to the relaxation of the ventricles, it's amplitude in range of (0.1–0.8 mV) and duration between (0.05–0.25 s). In Normal ECG recording PR interval is between (0.12–0.2 s) while normal QRS duration lies between (0.06–0.10 s), QT interval lies between (0.36–0.44 s). the QT interval between (0.36–0.44 s) and ST segment between (0.08–0.12 s). ECG is a non-stationary signal; it has multiple frequencies. The QRS wave oscillates faster than the T wave which is also faster than P wave. The ECG signal acquires noise from the power supply and interference from breathing muscle, which have to be removed before processing of ECG signals. So it's very difficult to analyze ECG signal, beside that the clinical observation takes long time. According to this automatic analysis of ECG signal is preferred to done by computers. Arrhythmias is the oddity of the ECG signal from the above normal measurements and specifications, it reflects a fast or slow heart beats (tachycardia, bradycardia) or irregular ECG patterns.

Ventricular arrhythmias are the popular type of cardiac arrhythmias leading to abnormal heartbeat causing approximately 79% of sudden death. As soon as the arrhythmia is detected the cardiac arrest can be avoided. Therefore, it is safe to conclude that regular heart rate monitoring is essential to prevent cardiovascular disease. Arrhythmia detection in ECG signals has attracted many researchers [4]. Nowadays, automated diagnostic systems of heart disease are widespread, ranging from choosing the most powerful suffering factors to physicians in making independent decisions. In addition to the unseen morphological features, wavelet, and mathematical features have also been proven to be effective in diagnosis [16]. During last years, different algorithms of machine learning provide accurate ECG signal analysis [17], making ECG analysis more brilliant and effective [18]. Many methods have been proposed for identifying cardiac arrhythmias with advantages and drawbacks. The next section of the paper presents a literature review of arrythmias classification.

We present a new approach to improve arrhythmia classification prediction accuracy. We employed the dipper throated optimization algorithm for optimizing the feature selection and the K-nearest neighbors' classifier for categorizing patients into one of 16 arrhythmia types. The medical industry can benefit greatly from this approach to arrhythmia categorization. The categorization helps in determining if an arrhythmia exists or not. The dataset for the simulation came from the UCI Machine Learning arsenal, and the results showed a significant improvement in classification accuracy.

The following is how the rest of the paper is organized. The basis of arrhythmia categorization is discussed in Section 2. The method and strategy proposed are explained in Section 3. The simulation results for the suggested technique are presented in Section 4. Section 5 concludes this work by summarizing the results and suggesting areas for further investigation.

2 Literature Review

Several methods for detecting and classifying cardiac arrhythmia have been presented in the last two decades. Simple statistical learning, traditional machine learning, and more contemporary deep learning techniques are all examples of these approaches.

Filtering to remove noise from ECG [19], signal segmentation [20], and feature extraction [21] are the most used methods to detect arrhythmia. Different researchers classify arrhythmias using machine learning (ML) and data mining, we will now discuss several proposed algorithms. The first research used discrete wavelet transform to identify QRS, reduce the noise using empirical modern distribution and classify five types of arrythmias using support vector machine (SVM) with 98% accuracy of 99% sensitivity [22]. Another research used statistics and Hermite coefficient in detection of QRS and SVM to classify

5 different types of arrhythmia with 98% averaging accuracy. Although the high accuracy but this method suffers from high computation cost. Another Algorithm used higher order multidimensional Fourier transform for feature extraction, and SVM to classify five different types of arrhythmia with 99% accuracy [23]. Also, a higher order multidimensional Fourier transform for feature extraction, and SVM for classification are used in [24]. A new idea used a least square support vector machine in the classification process suggested in [25].

Particle swarm optimization (PSO)is used to increase the performance of SVM in classification of five types of arrhythmia by fine tune the discriminator function for selecting the best features is introduced in [26]. The authors adopted their algorithm to two existing classifiers the first one is K-nearest neighbors (KNN) while the second is radial basis function neural networks. Genetic algorithm is used to optimize the discriminator function, and modified SVM for classification of arrythmia is used in [27]. Authors in [28] proposed a least square SVM classifier to classify heartbeat with 96% accuracy. Discrete wavelet transform is used for feature representation with SVM classifier to classify five types of arrhythmias with 98% accuracy is proposed in [29]. A random decision forest classifier and discrete cosine transform for detecting R-R interval are proposed as a new classifier for arrythmia classification in [30].

A novel classifier is proposed to classify seventeen different types of arrhythmias [30]. It works in two steps; the first by identifies the P wave and the QRS complex using the Pan-Tompkins method, while the second step KNN classifier is used to classify them. A Graphic Processing Unit based cloud system used for arrhythmia classification with two stages as in [31] is presented in [32]. Machine learning model are strongly affected by feature architecture and extraction. Basic idea after learning to incorporate all data in ECG signals for the ML algorithm to read and select functions. This theory also supports the deep learning model, especially convolutional neural network and its 1-D equivalent [33]. As a result of the power and optimism of deep learning strategies, researchers [34–36] use these methods for the classification of different types of diseases. A conventional neural network (CNN) model for prediction of heart attack with 95% is presented in [37]. A proposed automated classifier for arrhythmias introduces in [38]. Another proposed automated CNN model is built for classification of ventricular arrhythmias with 93% accuracy, 95% sensitivity is presented in [39].

A suggested algorithm used short term Fourier transform and wavelet transform for the classification of arterial fibrillation. Also, a CNN model is built to interpret ECG segments [40]. Another proposed algorithm uses 5-layer CNN to classify arrhythmias which provides accuracy but have a problem of vanishing gradient [41]. A proposed end to end CNN model is built for the classification of cardiac arrest during cardiopulmonary resuscitation with 89% accuracy for ventricular fibrillation [42]. Another research used convolution deep neural network for the classification of arrythmia and optimization using random search is presented in [43]. Two deep neural network architectures are used to classify electrical activity and generating rhythm using ECG reading and used Bayesian optimizer and provide 93% accuracy proposed in [44]. A proposed algorithm for classification of atrial fibrillation that includes connections in CNN, which increase the speed of data transmission and reduces the dependencies between data presented in [45]. three different algorithms: CNN, CNN+LSTM and CNN+ LSTM+ attention is proposed for the arrhythmia classification presented in [46,47]. Another algorithm proposed a CNN-LSTM model with converting the ECG signal into the time and frequency domain to train his model presented in [48] and achieves 89% accuracy. Tab. 1 presents a summary of the electrocardiogram classification methods in the literature.

Table 1: Summary of the electrocardiogram classification methods in the literature

Ref.	Database	Method	ACC (%)	Sensitivity (%)	Specificity (%)
[30]	MIT-BIH arrhythmia	CNN	96.00	95.49	94.19
[31]	MIT-BIH arrhythmia	CNN-LSTM	98.00	97.87	98.57
[32]	MIT-BIH arrhythmia	Optimize CNN	93.19	93.98	95.00
[33]	ECG (Shaoxing Hospital)	CNN	93.19	95.00	94.30
[34]	MIT-BIH arrhythmia	CNN with focal loss	98.55	82.00	79.00
[35]	MIT-BIH arrhythmia	CNN with focal loss	97.40	96.7	97.8
[36]	MIT-BIH arrhythmia	CNN	95.30	94.2	95.00
[37]	China ECG Challenge	Cascade CNN	86.50	85.3	82.00
[38]	MIT-BIH arrhythmia	SVM	99.51	99.28	99.63
[39]	MIT-BIH arrhythmia	CNN	97.16	99.28	99.63
[40]	MIT-BIH arrhythmia	CNN	97.38	92.00	95.63

3 Methodology

In this paper, we propose the application of the dipper throated optimization (DTO) algorithm to select the significant features of the given dataset. In addition, we employed DTO algorithm to optimize the parameters of the K-NN classification algorithm. Practically, the process starts with preprocessing the records of the dataset to ensure the consistency and integrity of the recorded data. The coming sections present the main steps of the proposed approach.

3.1 Preprocessing

In contrast to those characteristics with tiny numeric values, the features in the arrythmia dataset have huge numeric values, which have a significant impact on classification accuracy. For many attributes in the dataset utilized in this research, there is an inclusive numeric fluctuation. For these sorts of characteristics, data normalization is employed to limit the effect of the response variables. Data normalization aims to improve the classification model's performance by limiting the impact of higher-valued features. The numeric stability of the proposed approach is improved by using a scaling and centering strategy for data normalization [49].

3.2 Dipper Throated Optimization Algorithm

This algorithm is proved as an efficient metaheuristic optimization algorithm inspired by the hunting dipper throated bird that performs rapid bowing movements. The main formulation of this algorithm is expressed in terms of the following equations [50].

$$X = \begin{bmatrix} X_{1,1} & X_{1,2} & X_{1,3} & \dots & X_{1,d} \\ X_{2,1} & X_{2,2} & X_{2,3} & \dots & X_{2,d} \\ X_{3,1} & X_{3,2} & X_{3,3} & \dots & X_{3,d} \\ \dots & \dots & \dots & \dots & \dots \\ X_{m,1} & X_{m,2} & X_{m,3} & \dots & X_{m,d} \end{bmatrix} \tag{1}$$

$$Y = \begin{bmatrix} Y_{1,1} & Y_{1,2} & Y_{1,3} & \dots & Y_{1,d} \\ Y_{2,1} & Y_{2,2} & Y_{2,3} & \dots & Y_{2,d} \\ Y_{3,1} & Y_{3,2} & Y_{3,3} & \dots & Y_{3,d} \\ \dots & \dots & \dots & \dots & \dots \\ Y_{m,1} & Y_{m,2} & Y_{m,3} & \dots & Y_{m,d} \end{bmatrix} \tag{2}$$

$$h = \begin{bmatrix} h_1\left(X_{1,1}, X_{1,2}, X_{1,3}, \dots, X_{1,d}\right) \\ h_2\left(X_{2,1}, X_{2,2}, X_{2,3}, \dots, X_{2,d}\right) \\ h_3\left(X_{3,1}, X_{3,2}, X_{3,3}, \dots, X_{3,d}\right) \\ \dots \\ h_m\left(X_{m,1}, X_{m,2}, X_{m,3}, \dots, X_{m,d}\right) \end{bmatrix} \tag{3}$$

$$X(i+1) = \begin{cases} X_{best}(i) - K_1.|K_2.X_{best}(i) - X(i)| & \text{if } R < 0.5 \\ X(i) + Y(i+1) & otherwise \end{cases} \tag{4}$$

$$Y(i\ +\ 1) = \ K_3 Y(i) + \ K_4 r_1 (Xbest(i) - \ X(i)) + \ K_5 r_2 (XGbest\ -\ X(i)) \tag{5}$$

where the location and speed of the i^{th} bird in the j^{th} dimension are denoted by $X_{i,j}$ and $Y_{i,j}$ for $i \in 1, 2, 3, \dots, m$ and $j \in 1, 2, 3, \dots, d$. For each bird, the values of the fitness functions $h = h_1, h_2, h_3, \dots, h_n$ are used to find the best values of locations and speed of each bird, which is used to find the best solution. The steps of the dipper throated optimization algorithm are depicted in Fig. 2.

3.3 Feature Selection

The challenge in selecting features is unique since the search space is limited to two binary values, 0 and 1. Consequently, we used the sigmoid function to turn the normal optimizer's output into something that works for our purpose. To fit the feature selection problem, we apply the following equation to transform the continuous solution to binary.

$$\begin{aligned} &S^{(i+1)} = \begin{cases} 0 & \text{if } Sigmoid(S_{Best}) < 0.5 \\ 1 & otherwise \end{cases} \\ &Sigmoid(S_{Best}) = \frac{1}{1 + e^{-10(S_{Best} - 0.5)}} \end{aligned} \tag{6}$$

where $S^{(i+1)}$ is the updated binary position at iteration i and S_{Best} is the best position retrieved by the dipper throated optimization algorithm.

3.4 K-Nearest Neighbors Classifier

The query instance's KNN prediction is based on the category of nearest neighbors' simple majority. To calculate the K-nearest neighbors, it uses the shortest distance between the query instance and the training examples. Euclidean distance, which is defined in the following equation, is a widely used distance metric.

$$d^2{}_{ij}(n) = \sum_{m=1}^{M} \left\{x_i(n,\ m) - \ x_j(n,\ m)\right\}^2 \tag{7}$$

where the training set is denoted by $x_i(n, m)$ and the testing set is denoted by $x_j(n, m)$ for n^{th} sample and m^{th} feature dimension. The detailed steps of KNN classifier are shown in Fig. 3.

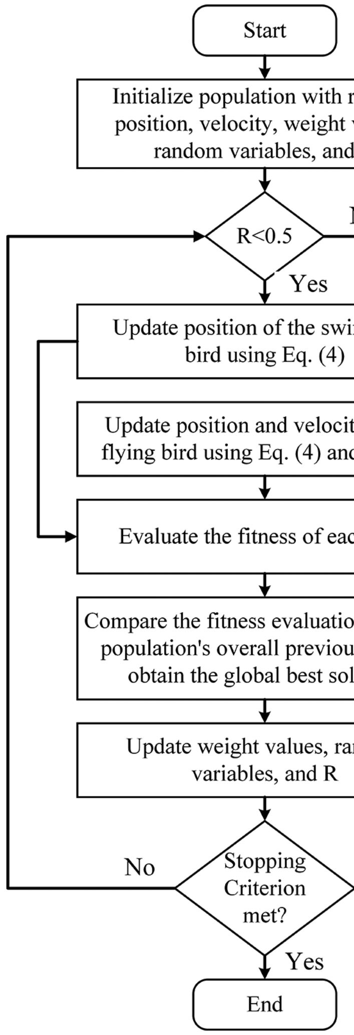

Figure 2: The steps of the dipper throated optimization algorithm

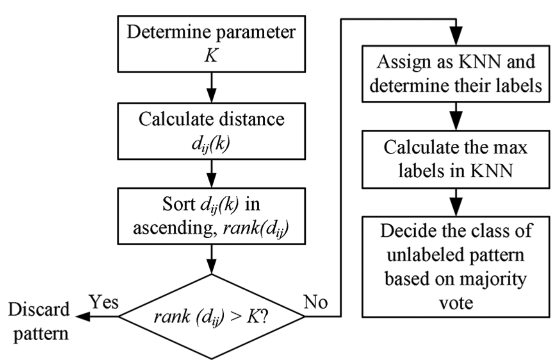

Figure 3: The steps of the K-nearest neighbors' classifier

4 Experimental Results

The UCI ML Repository [27] provided the dataset. There is a total of 452 of them. Each row represents a separate patient's medical data. 279 characteristics, including as weight, height, and age, are included in the electrocardiography-related dataset. Our major objective was to classify arrhythmia recordings into 16 different types based on their presence or absence. The normal ECG was represented by class 01 of arrhythmia, whereas classes 02 through 15 indicated various pathological classes of arrhythmia, and class 16 represented an unidentified group of patients. As illustrated in Fig. 4, a considerable number of classes are uncategorized, with 245 examples belonging to class 01 and 185 instances dispersed among 14 different types of arrhythmia classes [51,52].

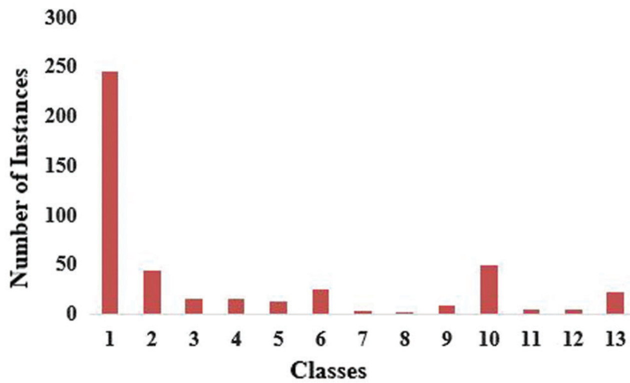

Figure 4: Arrhythmia instances distribution in several classes

To prove the effectiveness of the proposed approach, a set of experiments were conducted to assess the performance of the steps of the proposed approach. The first experiment was conducted to assess the feature selection process using the dipper throated optimization algorithm. The results presented in Tab. 2 records the achieved findings using the proposed approach with comparison to other six feature selection algorithms. As shown in this table, the results achieved by the proposed approach outperform those achieved by the other algorithms.

Table 2: The performance of the feature selection algorithms

	bDTO	bGWO	bPSO	bBA	bWAO	bFA	bGA
Average error	0.6310	0.6482	0.682	0.6916	0.6818	0.6804	0.6618
Average Select size	0.5838	0.7838	0.7838	0.9232	0.9472	0.8183	0.7262
Average Fitness	0.6942	0.7104	0.7088	0.7317	0.7166	0.7607	0.7218
Best Fitness	0.5960	0.6307	0.6891	0.6214	0.6807	0.6794	0.6251
Worst Fitness	0.6945	0.6976	0.7568	0.7230	0.7568	0.7770	0.7402
Standard deviation Fitness	0.5165	0.5212	0.5206	0.5305	0.5228	0.5574	0.5228

On the other hand, to chose the classifier that is best convenient for the task in hand, three classifiers were evaluated to find the best classifier. Tab. 3 presents the assessment of the three classifiers. As shown in the table, the best performance was achieved by the KNN classifier. Therefore, this classifier is adopted for the optimization and classification of the dataset in hands.

Table 3: The performance of three machine learning classifiers

	KNN	SVM	NN
AUC	0.951	0.946	0.938
MSE	0.000289	0.000311	0.000116

Another set of experiments is conducted to evaluate the performance of the optimization applied to the KNN classifier. In these experiments, five optimization approaches were used to optimize the parameters of KNN classifier, and the results are recorded in Tab. 4. In this table, a statistical analysis is presented. The results achieved by the proposed approach are shown as the best results among the other results achieved by the other approaches.

Table 4: Statistical analysis of the results achieved by optimizing the KNN classifier

	DTO+KNN	WOA+KNN	GWO+KNN	GA+KNN	PSO+KNN
Number of values	13	13	13	13	13
Minimum	0.998	0.9551	0.956	0.969	0.961
25% Percentile	0.999	0.971	0.976	0.989	0.981
Median	0.999	0.971	0.976	0.989	0.981
75% Percentile	0.999	0.971	0.976	0.989	0.981
Maximum	0.999	0.981	0.9786	0.989	0.981
Range	0.001	0.0259	0.0226	0.02	0.02
Mean	0.9988	0.9705	0.9747	0.9867	0.9787
Std. Deviation	0.0003755	0.005402	0.005653	0.005991	0.005991
Std. Error of Mean	0.0001042	0.001498	0.001568	0.001662	0.001662
Coefficient of variation	0.03760%	0.5566%	0.5800%	0.6072%	0.6122%

The Wilcoxon signed rank test is performance to measure the statistical difference between the proposed approach and the other approaches. Tab. 5 presents the results of this analysis. The recorded results emphasize our expectations and show that there is no statistical difference between the proposed and other approaches.

In addition, the one-way analysis of variance (ANOVA) test is performed to study difference between the proposed approach and the other approach using different hypothesis. The results are shown in Tab. 6.

Moreover, Fig. 5 shows six plots that deeply investigate the performance of the proposed approach. The first three plots Figs. 5a–5c depict the robustness of the proposed approach. The other three plots Figs. 5d–5f depict the superiority of the proposed approach in comparison to the other approaches.

Table 5: Wilcoxon signed rank test of the results achieved by optimizing the KNN classifier

	DTO+KNN	WOA+KNN	GWO+KNN	GA+KNN	PSO+KNN
Theoretical median	0	0	0	0	0
Actual median	0.999	0.971	0.976	0.989	0.981
Number of values	13	13	13	13	13
Wilcoxon signed rank test					
Sum of signed ranks (W)	91	91	91	91	91
Sum of positive ranks	91	91	91	91	91
Sum of negative ranks	0	0	0	0	0
P value (two tailed)	0.0002	0.0002	0.0002	0.0002	0.0002
Exact or estimate?	Exact	Exact	Exact	Exact	Exact
P value summary	***	***	***	***	***
Significant (alpha = 0.05)?	Yes	Yes	Yes	Yes	Yes
How big is the discrepancy?					
Discrepancy	0.999	0.971	0.976	0.989	0.981

Table 6: ANOVA test of the achieved results

ANOVA table	SS	DF	MS	F (DFn, DFd)	P value
Treatment (between columns)	0.006523	4	0.001631	F (4, 60) = 61.27	$P < 0.0001$
Residual (within columns)	0.001597	60	2.66E-05		
Total	0.008119	64			

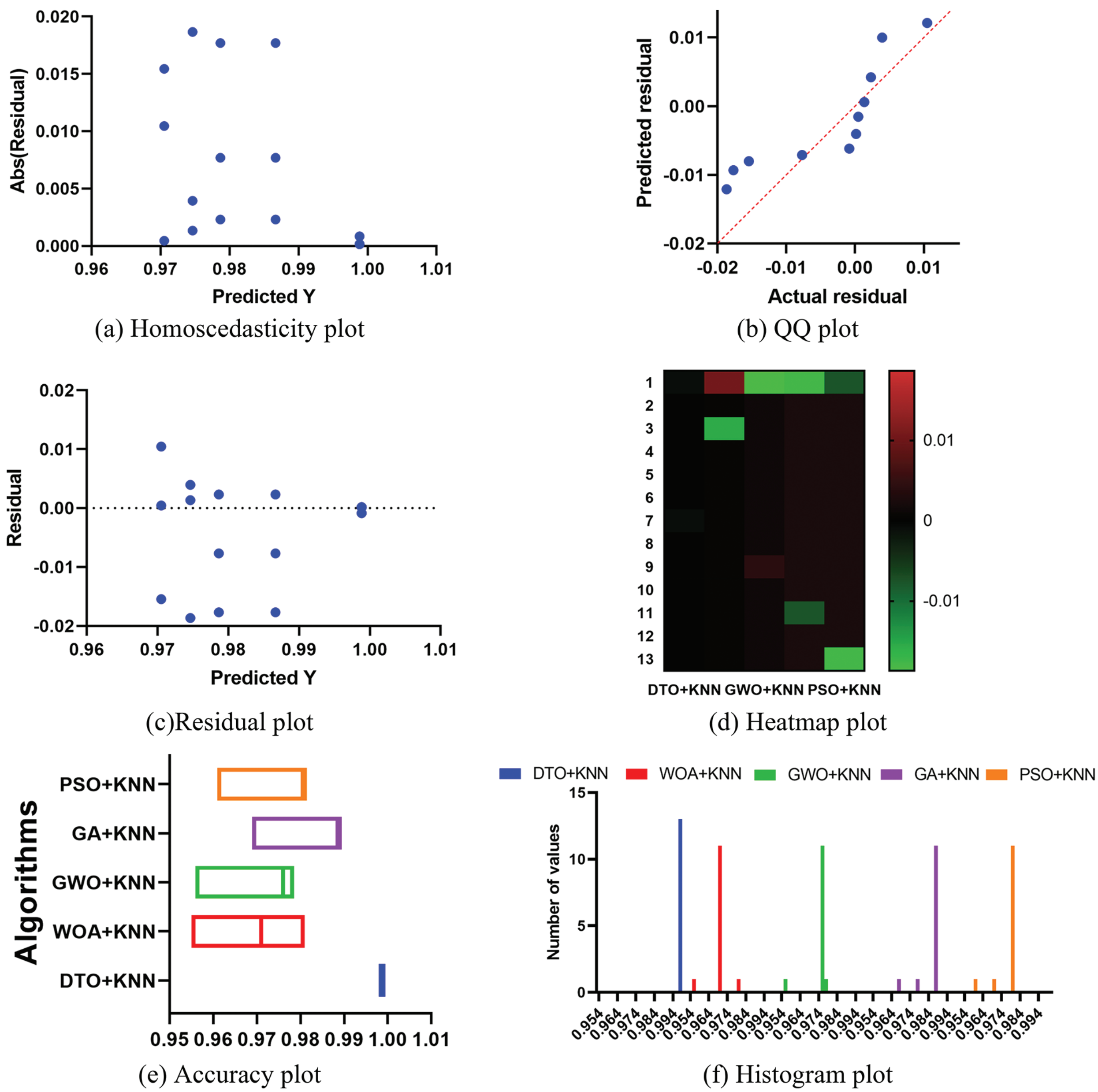

Figure 5: Performance evaluation of the proposed approach with comparison to the other approaches

5 Conclusions

In this paper, we proposed a new approach for categorization of arrhythmia based in the dipper throated optimization algorithm. This algorithm is used for both feature selection and optimization of the parameter of the KNN classifier. The proposed approach outperformed the earlier ML and optimization frameworks in terms of accuracy. The UCI ML repository provided the arrhythmia dataset. It planned to use this optimization approach with clustering and noise reduction methods in other domains in the future. Because the majority of the examples in the dataset utilized in this study belong to class 1 and the other classes only contain two to three instances, the risk of misclassification is increased when applying different methods. Because Class 1 has the most impact on the prediction model's output, obtaining as many cases in the other classes as feasible is required to improve forecasts in the future. If the arrhythmia dataset characteristics were categorized based on their physical similarity, the algorithm's result would be more helpful. Cases with aberrant P waves, for example, may be grouped together, whereas all variables with abnormal Q waves could be grouped together. After then, the results of various methods might be compared.

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