An Improved Firefly Optimization Algorithm for Analysis of Arrhythmia Types

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Abstract— Irregular heartbeats rhythm is the result of arrhythmia condition which can be a threat to life if not treated at the early stage. If it is necessary to know the type of arrhythmia to treat the patient appropriately. The traditional method is complex and an efficient algorithm is required to diagnose. An improved firefly optimization algorithm is proposed to analyze arrhythmia types. Four performance measures confirm the model's effectiveness and experimental evaluation shows that it achieves a sensitivity of 86.27%, accuracy of 86.14%, precision of 87.52%, and specificity of 87.37% in arrhythmia-type classification. The algorithm can effectively classify the arrhythmia types with high accuracy and specificity.

Keywords- Improved Firefly Optimization Algorithm (IFOA), MLPT, EEMD, Lévy-flight firefly algorithm (LF-FA), Hjorth parameters

I. INTRODUCTION

The electrical activity of heart is recorded by noninvasive device and the recorded signal is weak non-stationary ECG signal. While diagnosing different artifacts like baseline drift, electrosurgical noise, and electrode contact noise will get interfere and make it difficult to diagnose the arrhythmia type [3]. The importance of ECG signal in diagnosing arrhythmia is discussed in the research work.

A new Improved Firefly optimization Algorithm (IFOA) is presented to extract the features of the arrhythmia types. IFOA model uses MLPT and EEMD techniques for signal transformation and decompose the signal. Firefly optimization algorithm (FOA) extracts features using standard deviation, zero crossing rate, mean curve length, Hjorth parameters, mean teager energy, and log energy entropy [5-9] [11]. Feature reduction is also done by IFOA model by using intermittent scale-free search pattern i.e, Lévy flight style for optimal feature selection [12-14]. The research work shows the effectiveness and robustness of the IFOA model in terms of specificity, precision, sensitivity, and accuracy.

[15-16] The multi-class support vector machine (MSVM) is a machine learning method which depends on the Vapnik-Chervonenkis (VC) dimension theory and the other one is the structural risk minimization principle from statistical learning theory. Authors use different eigenvalues and Kernel functions of MSVM to classify normal heartbeat from atrial premature contraction (APC), ventricular premature beat (VPC), right bundle branch block (RBBB), and left bundle branch block (LBBB). Training results will be different as the MSVM method depends on different kernel functions.

Saumendra et al. [19] used a random forest algorithm to detect tachycardia. The result shows the sensitivity and specificity of the classifier and further accuracy can be improved by modifying the technique. To overcome the drawback of entering the number of trees manually as a parameter, the researchers [18] introduced an enhanced random forest method that uses simulated annealing (SA) algorithm for an optimal number of trees calculation. The enhanced random forest method needs to be analysed with the other classifiers. A random forest network is proposed by Van Nam Pham [17], which is used to analyse and classify the ECG signals. The classified signals help to detect arrhythmias.

K-Nearest Neighbor (KNN) algorithm has been proposed by Indu Saini et al. [22] as a classifier to detect the QRS-complex in ECG signals. In addition to the detection, the authors try to find the accuracy, sensitivity, and specificity using KNN and found that the proposed algorithm is reliable and accurate for the detection of the QRS complex. Further, the algorithm can be enhanced to find the specific rhythms in ECG signals. [20] The authors performed ECG signal processing, feature extraction, and classifier as KNN to achieve the high accuracy of the proposed method when compared to other machine learning

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algorithms. Toulni Youssef et al. [21] used the discrete wavelet transform (DWT) as a mother wavelet with the Symlet 8 to establish the model with the classifier as the K Nearest Neighbors and found that the accuracy to identify the ECG signals is high.

Researchers proposed [23] Neural Networks methods such as CNN and RNN to classify the ECG signals accuracy of the proposed method is better when compared with the K-NN and SVM classifiers. To achieve high precision and accuracy machine learning methods need to be improved.

II. METHODOLOGY

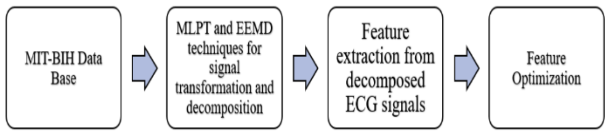

Fig. 1. Flow diagram of the proposed work

Arrhythmia refers to any irregularity in the rhythm or rate of the heartbeat, and [10] ECG signals are used to measure the electrical activity of the heart. The flow diagram of the proposed work is shown in Fig. 1, it includes four steps:

- The research work uses MIT-BIH arrhythmia databases, it consists recording of 48 different sets of heart diseases. Each recorded set is of 30 mins and sampled at a frequency rate of 360Hz [15].
- Signal Transformation and Decomposition: This step involves transforming the ECG signals into a format that is suitable for analysis and decomposing signals into component parts using two techniques: the Multilayer Perceptron Transform (MLPT) and the Ensemble Empirical Mode Decomposition (EEMD).
- Feature Extraction: This step involves extracting various features from the decomposed ECG signals, which are then used to classify arrhythmia types. The features include standard deviation, zero-crossing rate, Hjorth parameters, mean Teager energy, log energy entropy, and mean curve length.
- Feature Optimization: This step involves optimizing the extracted features using the Improved Firefly Optimization Algorithm (IFOA), which is a metaheuristic optimization algorithm.

The flow diagram shown in Fig 1., shows the framework of the proposed specifies the sequence of steps involved in the classification of arrhythmia types. The flow diagram visually represents the proposed framework, including the four steps mentioned above, as well as the inputs, outputs, and processing of the data at each stage. The diagram is a useful tool to understand the proposed framework and the overall process involved in classifying arrhythmia types using ECG signals.

A. MLPT-EEMD

The heart disease can be diagnosed by using noninvasive Electrocardiographic device which records electrical activity of heart. Arrhythmia can be detected at the early stage with help of these recordings. The recording contains important information which are complex and difficult to interpret. Multiscale Local Polynomial Techniques and Ensemble Empirical Mode Decomposition techniques are used for transformation and decomposition of the recorded ECG signals.

Multiscale Local Polynomial Techniques (MLPT) is wavelet transformation method used for non-equispaced data [4]. Complex signals are made simpler by multi-scale decomposition technique and it will smooth the signal during reconstruction. ECG signals are decomposed into number of Intrinsic mode functions (IMFs) by Empirical Mode Decomposition (EMD) technique [25-26]. In this method, high and low frequencies are decomposed into lower-order and higher-order IMFs components respectively. In general, low-frequency noises are by baseline wander and high-frequency noises are by power line interference, denoising of these signals is easily done by decomposing data. Further, the scale separation problem is overcome by Ensemble Empirical Mode Decomposition (EEMD) technique.

Complex ECG signals can be analysed using MLPT and EEMD and useful information is extracted for diagnosis of arrhythmia types. Fig 2. shows the result of decomposition and smoothing by MLPT and EEMD technique and process is as follows:

1. White noise n(t) is added in series to the input signal $x(t)$, then $x_n(t) = x(t) + n(t)$
2. EMD algorithm decomposes the noisy signal $x_n(t)$ into intrinsic mode functions (IMFs)
3. Steps 1 and 2 are repeated for N iterations to get $IMF_k^i(t)$
4. Step 3 is repeated, in each trial series of white noise is considered to obtain the $IMF_k^i(t)$.

   where $IMF_k^i(t)$ is the kth mode of the ith trial;
5. The ultimate Intrinsic Mode Functions (IMFs) are acquired by taking the average of the set of IMFs that correspond to each experiment as given by eqn. (1).

$$IMF_k(t) = \frac{1}{Nt}\sum_{i=1}^{N} IMF_k^i(t) \quad (1)$$

where N is the trials number.

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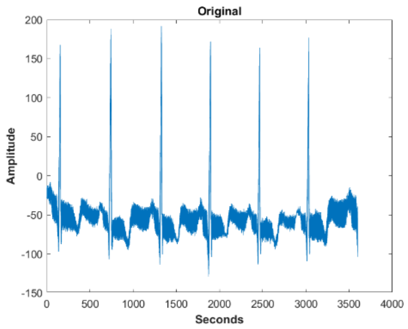
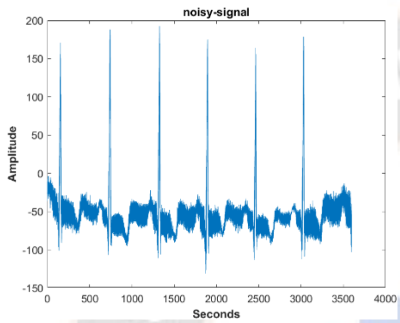
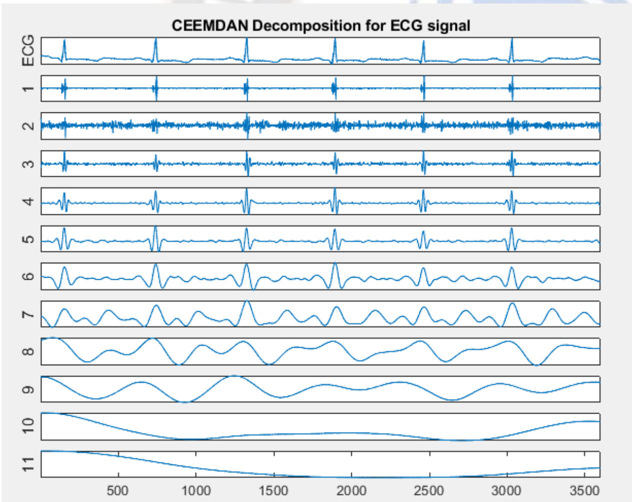


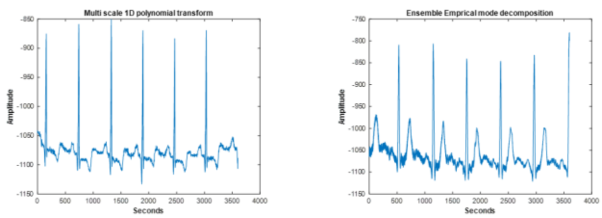
(a) Original ECG signal



(b) Noisy Signal



(c) Decomposed ECG signal



(d) MLTP-EEMD denoising signal

Fig 2. Result of MLPT-EEMD (a) Original ECG signal; (b) Noisy Signal; (c) Decomposed ECG signal; (d) MLTP-EEMD denoising signal

B. Feature Extraction

After decomposing the ECG signals using MLPT and EEMD techniques, feature extraction is performed to capture different aspects of ECG signal. The following methods are used for feature extraction:

- The log energy entropy, which characterizes the non-linear dynamics of the ECG signal [30]. This technique allows to extract information about the heart's function and behavior of the ECG signal.
- Number of times the signal crosses the mean value within a three-second-long moving average [6] is counted using zero crossing rate technique. This technique provides information about the rate at which the ECG signal is changing over time.
- [7] Hjorth parameters technique, consists of three-time domain features: complexity, mobility, and activity. The activity is determined as the standard deviation of the epoch, and the mobility is defined as the ratio of the activity of the epoch to the derivative activity of the epoch. Complexity, on the other hand, is defined as the ratio of the activity of the epoch to the derivative mobility of the epoch. The Hjorth parameters provide information about the activity, mobility, and complexity of the ECG signal.
- The mean curve length [8], which is the linear distance between successive points on the curve. This technique provides information about the shape and smoothness of the ECG signal.
- Mean Teager energy [9], which is a non-linear operator and used to obtain energy of the signal based on mechanical and physical considerations. The Teager energy operator tracks the amplitude envelopes and instantaneous frequencies of the ECG signal, providing information about its energy content.
- Further, information about ECG signal is obtained by using continuous form of the Teager energy operator.

All these feature extraction techniques allow to capture a broad range of information about the ECG signal, including its non-linear dynamics, rate of change, activity, mobility, complexity, shape, and energy content.

The output of the Teager energy operator gives effective energy fluctuation because of its excellent time resolution. Finally, the standard deviation measures how far the ECG signals deviate from the mean value. The extracted 32 features are given to the improved IFOA for feature optimization that helps in decreasing the system complexity and computational time.

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C. Feature Optimization

The Feature Optimization Algorithm (FOA) is a type of swarm intelligence algorithm which is encouraged by the flashing behavior of fireflies. The algorithm is designed to optimize the features extracted from ECG signals by mimicking the characteristics of firefly behavior. In the FOA, the population of fireflies represents the luminary flashing activity of fireflies, which is used to communicate, attract mates, and warn of predators.

The brightness value of the fireflies in the FOA is determined using the landscape of the objective functions. This value represents the fitness of the fireflies in the population. The fireflies are unisex, and each firefly is attracted to the other regardless of sex. The attractiveness of a firefly is proportional to its brightness value, meaning that less bright fireflies are attracted to more bright fireflies.

The FOA also considers the distance between fireflies in determining their attractiveness. As the distance between fireflies increases, their attractiveness and brightness decrease proportionally. This relationship is determined using absorptions and the inverse square law. The light intensity (l(x)) is mathematically defined in equation (4).

Overall, the FOA is a nature-inspired optimization algorithm that simulates the flashing behavior of fireflies to optimize the features extracted from ECG signals. By using the brightness value and attractiveness of fireflies, the FOA can effectively search for the optimal feature set for arrhythmia classification [11].

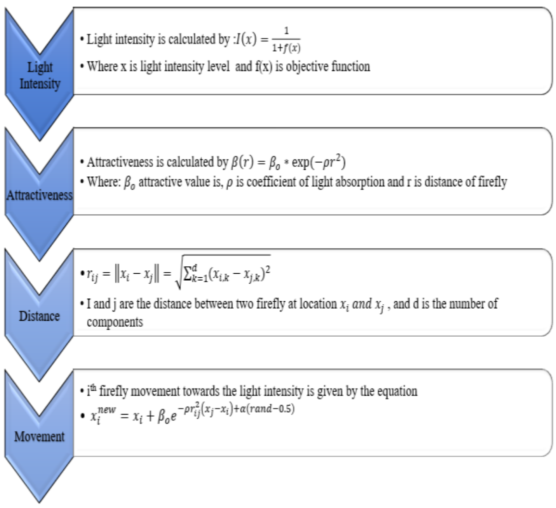

Fig 3. FOA algorithm

Firefly optimization algorithm usually gets trapped by the local optimization and this can be overcome by considering fruit flies navigate tricky landscapes by taking short, straight flights and then suddenly turning. This inspires another method called the Lévy-flight firefly algorithm (LF-FA) that uses a similar pattern to explore more possibilities and find better solutions. Instead of always moving randomly in all directions, LF-FA uses a special type of randomness called Lévy distribution to decide which way to go. Therefore, the Improved Feature optimization algorithm (IFOA) has been developed using Lévy distribution and the updated position is by the given equation (2).

$$x_i^{new} = x_i + \beta_o e^{-\rho r_{ij}^2 (x_j - x_i) + \alpha(rand - 0.5)} \otimes \ Lévy \qquad (2)$$

Where α is the randomization parameter, $\alpha(\text{rand} - 0.5)$ gives random direction, ⊗ is the Hadamard product and the random step length is calculated by the Lévy flights. The Lévy flight distribution and the Lévy random number are specified in equations (3) and (4).

$$Lévy(\eta) \sim \mu = t^{1-\eta}, (0 \leq \eta \leq 2) \qquad (3)$$

Random value for $Lévy$ is calculated by,

$$Lévy(\eta) \sim \frac{\phi * \mu}{|\nu|^{1/\eta}} \qquad (4)$$

Where ν and μ are the standard normal distributions, and φ is calculated as follows in equation (5),

$$\phi = \left[\frac{\tau(1+\eta) * \sin\left(\frac{\pi\eta}{2}\right)}{\tau((1+\eta)/2 * \eta x 2^{\eta + \frac{1}{2}}}\right]^{1/\eta} \qquad (5)$$

Where τ is standard Gamma function, and η = 1.5

The research work is measured by four performances namely: specificity, precision, sensitivity, and accuracy. These measures are derived from four concepts: False Negative (FN), False Positive (FP), True Positive (TP), and True Negative (TN). Using these concepts, the accuracy, precision, sensitivity, and specificity are calculated as shown in equation (6), (7), (8) and (9) respectively to classify the arrhythmia type.

$$Accuracy = \frac{TN + TP}{TN + TP + FP + FN} \qquad (6)$$

$$Precision = \frac{TP}{TP + FP} \qquad (7)$$

$$Sensitivity = \frac{TP}{TP + FN} \qquad (8)$$

$$Specificity = \frac{TN}{TN + FP} \qquad (9)$$

III. Quantitative Analysis

This section investigates the performance of the IFOA model on the MIT-BIH database. The analysis employs four classifiers, namely random forest, Multi-SVM (MSVM), CNN, Random Forest, and K-Nearest Neighbor (KNN). Simulation results for these classifiers, with and without the IFOA, are shown in Table

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1and 2. The IFOA model achieved better arrhythmia classification compared to other classifiers, with a sensitivity of 86.27%, accuracy of 86.14%, precision of 87.52%, and specificity of 87.37%. These simulation outcomes are higher than those obtained with traditional classifiers. Figure 4 and 5 shows performance of the classifiers with and without the IFOA.

TABLE 1. SIMULATION RESULTS OF THE CLASSIFIERS WITHOUT IMPROVED FIREFLY OPTIMIZATION ALGORITHM

Without IFOA				
Classifiers	**MSVM**	**Random Forest**	**KNN**	**CNN**
Accuracy (%)	85.58	93.08	89.86	88.72
Precision (%)	83.51	92.53	87.93	87.84
Sensitivity (%)	84.21	93.39	88.51	89.45
Specificity (%)	85.14	94.43	90.19	88.63

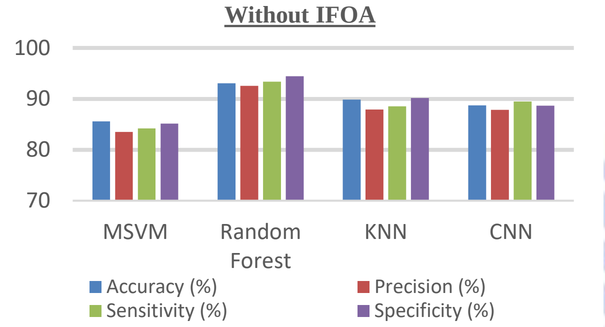

Fig. 4 Performance of classifiers without IFOA

TABLE 2. SIMULATION RESULTS OF THE CLASSIFIERS WITH IMPROVED FIREFLY OPTIMIZATION ALGORITHM

With IFOA				
Classifiers	**MSVM**	**Random Forest**	**KNN**	**CNN**
Accuracy (%)	86.14	95.03	90.99	81.50
Precision (%)	87.52	95.86	92.44	82.21
Sensitivity (%)	86.27	93.34	90.34	80.71
Specificity (%)	87.37	94.88	89.33	82.46

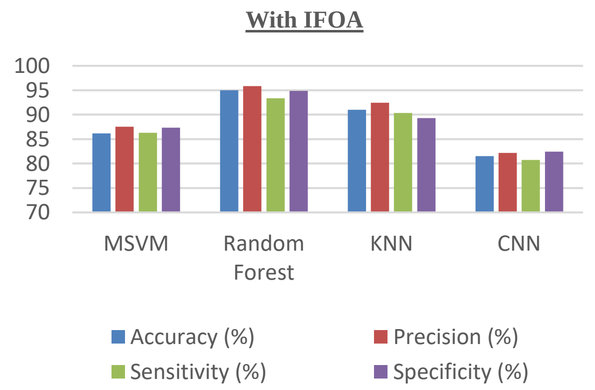

Fig. 5 Performance of classifiers with IFOA

Conclusion

The manuscript implements the IFOA model to classify arrhythmia types effectively. The model comprises four major steps: signal transformation and decomposition, feature extraction, feature dimensionality reduction, and classification. MLPT and EEMD techniques are used to transform and decompose the ECG signals obtained from the MIT-BIH database. Feature extraction is performed using standard deviation, zero crossing rate, mean curve length, Hjorth parameters, mean teager energy, and log energy entropy. The IFOA method is then employed to optimize the multidimensional feature values, which enhances system complexity and computational time. Four performance measures confirm the model's effectiveness, and experimental evaluation shows that it achieves a sensitivity of 86.27%, accuracy of 86.14%, precision of 87.52%, and specificity of 87.37%. in arrhythmia type classification, outperforming existing models. Future work involves classifying the heart beats types by DNN model.

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