Journal Pre-proof

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PII: S0169-2607(20)31440-1
DOI: https://doi.org/10.1016/j.cmpb.2020.105607
Reference: COMM 105607

To appear in: *Computer Methods and Programs in Biomedicine*

Received date: 4 April 2020
Accepted date: 9 June 2020

Please cite this article as: Dinesh Kumar Atal , Mukhtiar Singh , Arrhythmia Classification with ECG signals based on the Optimization-Enabled Deep Convolutional Neural Network, *Computer Methods and Programs in Biomedicine* (2020), doi: https://doi.org/10.1016/j.cmpb.2020.105607

HIGHLIGHTS

The arrhythmia classification is a significant research as WHO highlights the death-troll of persons with cardiac diseases to be around 17.3 million, which insist the conventional cardiac therapies to be useless. More importantly, the people with the cardiac problems are suffering a lot, requiring the need for an accurate classification strategy.

- The accurate classification is done using the deep CNN (Convolutional Neural Network), which is optimally tuned using the proposed BaROA (*Bat-Rider Optimization Algorithm*).
- Initially, the gabor, wave, and interval features are derived from the ECG signal and the feature vector is established.
- The feature vector is fed to the arrhythmia classification module, in which the extracted features are employed for deciding the patient to be with arrhythmia or no arrhythmia.
- The methods are analyzed using the MIT-BIH Arrhythmia Database and the analysis is performed based on the evaluation parameters, like accuracy, specificity, and sensitivity, which are found to be 93.19 %, 95 %, and 93.98 %, respectively.

Full Length Article

Arrhythmia Classification with ECG signals based on the Optimization-Enabled Deep Convolutional Neural Network

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***Abstract*-Arrhythmia classification is the need of the hour as the world is reporting a higher death troll as a cause of cardiac diseases. Most of the existing methods developed for arrhythmia classification face a hectic challenge of classification accuracy and they raised the challenge of automatic monitoring and classification methods. Accordingly, the paper proposes the automatic arrhythmia classification strategy using the optimization-based deep convolutional neural network (deep CNN). The optimization algorithm named, Bat-Rider optimization algorithm (BaROA) is newly developed using the multi-objective bat algorithm (MOBA) and Rider Optimization Algorithm (ROA).At first, the wave and gabor features are extracted from the ECG signals in such a way that these features represent the individual ECG features. Finally, the signals are provided to the BaROA-based DCNN classifier that identifies conditions of the individual as arrhythmia and no-arrhythmia from the ECG signals. The methods are analyzed using the MIT-BIH Arrhythmia Database and the analysis is performed based on the evaluation parameters, like accuracy, specificity, and sensitivity, which are found to be 93.19 %, 95 %, and 93.98 %, respectively.**

***Keywords:* Optimization, arrhythmia classification, deep convolutional neural network, Peak intervals, Gabor**

1. Introduction

The abnormality in ECG is a major significant factor that assists the prediction of cardiovascular diseases (CVDs) among the old and young population [9]. One of the common diseases is the cardiovascular arrhythmia that leads to sudden death under some cases when left untreated. The early warning of the states of the cardiac activity through real-time monitoring assists the life-saving and cares the health [1]. It is worth interesting to note that the abnormality in ECG of a person is a discontinuous symptom as the beats corresponding to arrhythmia emerges in a short time, which limits the diagnosis of the arrhythmia in hospitals. Additionally, the traditional monitoring system of the ECG often links the individuals with the instrument using a signal line; and for monitoring, a direct-wired connection is availed, whereas the wearable device using the wireless sensors is capable of monitoring the cardiac activity with no influence on the daily life of the user [10]. A huge amount of data is collected daily using the wearable device. The cardiologists engage themselves in the detection of the anomaly from the ECG waveform mainly, based on the rate of the heart beats, rhythm, and any variations in the morphological patterns. However, it is not feasible for inspecting the individual heart beat as there are number of heart beats, which raises the complexity of inspection and degrades the classification accuracy of the clinician [2]. Heartbeat Classification using ECG seems to be a valuable tool to study the cardiac arrhythmia, which appears to be one among the challenges in bio signal analysis [11] [4].

Cardiac arrhythmias result is a cause of the change in the heart beat rate, regularity, conduction or origin of electrical impulses, along with their symptoms ranging from minute palpitations to pain in the chest leading to the fainting of the person and causes death all-of sudden, which is based on the nature and aggressive state of the problem in individuals [12]. Arrhythmia causes a series of heartbeats with abnormal morphology or intervals. Thus, once the acquisition of the signal is done, the significant step is the heartbeat classification. The analysis by the human specialist does the long-term examination, which is time-consuming and is subjected to failures as a result of fatigue. Due to this reason, there is a requirement of the automatic method for classifying the heart beats and hence, diagnosing the person with arrhythmias require valuable support for the health-care professionals [13] [6].

The automatic system of heart-beat classification is grouped as four parts: signal preprocessing, detection of heart-beats and segmentation, feature extraction, and classification [26]. The features extracted from the data may be morphological features or any characteristic of ECG, heart beat intervals, independent component analysis (ICA), hermite polynomials, coefficients generated using the wavelets, and vector cardiogram (VCG) data [15, 13, 16]. Some of the existing features using the intervals between the beats and morphology are not enough for distinguishing the types of beat from others with appropriate precision [15]. There are various classifier models employed, such as self-organizing maps, support vector machines (SVMs), linear discriminants, learning vector quantization, neural networks, and extreme learning machines [19, 13] [6].

The classifiers, like linear discriminants depend on few assumptions regarding the data, such as linear separability and normal distribution [15]. SVMs are widespread classifiers and, based on the kernel function andit generates the decision regions able to attain independent performance in classification corresponding to the linear separability corresponding to the data. Additionally, SVM [34] is the used commonly employed models [14] [6]. There are several automatic methods that are developed for ECG classification. At present, there are several

Approaches employed for automatic ECG classification, like frequency analysis [16], mixture-of-experts method [18], k-Nearest Neighbour clustering [17], Artificial Neural Networks [20], Classification and Regression Trees [19], Hidden Markov Models [21], Support Vector Neural Network [32], Convolutional Neural Network [33], and SVM [22], Classification and Regression Trees [19], Probabilistic Neural Networks [23], recurrent NN (RNN) [24] and path forest [25]. In spite of the hectic efforts made for the automatic ECG assessment approaches, the performance was found to be better as a result of various reasons. At first, the ECG signals are affected due to different types of noises and physiological artifacts, like power line interference, baseline wanders, and muscle contraction [31]. The physiological artifact and noises assesses the ECG, which is difficult in case of the automatic computerized method. Additionally, the variations among the ECG signal of the individuals assure the inconsistency of the methods for classifying different subjects. Additionally, the time-varying dynamics and morphological features of ECG signals of the same individual enhance the difficulty existing with the automatic assessment method [26] [2].

The research concentrates on arrhythmia classification using the ECG signal of the individuals such that the perfect diagnosis of the patients is initiated. The arrhythmia classification is performed optimally using the deep neural networks, which is tuned optimally with an optimization algorithm. It is significant to note that the arrhythmia classification saves time to perform effective classification thus, enabling the early diagnosis of arrhythmia. The progressing steps in the arrhythmia classification include the feature extraction and feature classification. Initially, the ECG signal is subjected to the identification of the wave components in ECG using the multi-resolution wavelet-based approach [26].

Once the waves are identified using the ECG signal, the wave features are extracted that includes the intervals, PP, RR, PR, QT, and R peak. Additionally, the Gabor features are extracted using the Gabor filter. Finally, the wave and Gabor features establish the feature vector for feature classification. Finally, the classification is carried out using the deep neural network named as Deep CNN that is trained using the proposed BaROA and the classification depends on the features acquired from the ECG. The proposed BaROA algorithm is the integration of MOBA [27] and ROA [28] in such a way that the update equation of the bypass rider is interpreted for modification. The BaROA-DCNN classifier performs the arrhythmia classification in which BaROA tunes the Deep CNN classifier optimally.
The contribution in this research is demonstrated below:

Bat-Rider Optimization Algorithm-based deep Convolutional neural networks (BaROA-deep CNN): The arrhythmia classification is performed using the deep CNN that is tuned optimally using the proposed BaROA, which is the integration of the Bat algorithm in ROA.
The rest of the paper is structured as: motivation of the research is demonstrated in section 1 and the proposed method of arrhythmia classification is depicted in section 3 and the results are explained in section 4, discussion in section 5 and finally, section 6 concludes the paper.

2. Motivation

This section reviews the existing methods along with the merits and demerits and the key importance of the existing methods and challenges stood as the motivation of this research towards developing an effective method.

2.1 Literature review

The review of eight literature review papers is demonstrated in this section. Zhijian Chen *et al.* [1] developed a hybrid classifier using a weak linear classifier (WLC) and a strong support vector machine (SVM) classifier, which gained high accuracy and achieved higher energy saving capability. The drawback of the method was regarding the poor accuracy of the hybrid classifier. Yufa Xia *at al.* [2] developed an automatic system using the stacked denoising autoencoder (SDAE). The method was robust in classifying the ECG signals and in case of insignificant signal noise, the process of filtering would be enabled using this simple method. However, under the presence of the intricate noise, the method suffered to remove the noise. Xiaolong Zhai and Chung Tin [3] developed a method based on Convolutional Neural Network, which rendered highly reliable detection. Moreover, the method did not require any feature extraction strategy and did not demand any assistance from the experts. The drawback was regarding the robustness of the classification in case of the long-use applications. Tomás Teijeiro *et al.* [4] developed an automatic classification strategy based on the pure knowledge-based approach. The drawback of the method was regarding the ineffective beat labeling. Ping Cheng and Xiaodai Dong [5] used Support Vector Machines that possessed explicit physical significance and in addition, suffered from implementation complexity. The drawback of the method was regarding the real-time application of the template over online mode. João Paulo R.R. Leite and Robson L. Moreno [6] developed an automatic classification strategy that employed the amplitude, RR intervals, and Hjorth parameters, which rendered minimal computational cost and required simple steps for computation. The drawback of the method was regarding the classification of the normal beats that exhibited poor performance. Wei Li and Jianqing Li [7] developed a method, local deep field that enriched the deep learning strategy and in addition, competent for many other tasks holding similar characteristics. However, the drawback of the method was regarding the inability of the method for performing the general classification. Sandeep Raj and Kailash Chandra Ray [8] modeled the PSO Optimized support vector machine (SVM) in which the classifier parameters were tuned optimally, aiming at the maximal classification performance. The drawback of the method was regarding the extra computational time required for classification.
Fatma Murat *et al*. [35] developed a model for classifying the ECG data, which was used to effectively classify the five-class arrhythmia ECG dataset. Anyhow, the power consumption of this method was high. Özal yıldırım *et al*. [36] proposed a model for ECG signal analysis, which had high accuracy and required minimum classification time. However, this method was only applicable for the ECG signal which contains one class. Pranav Rajpurkar *et al.* [37] developed an algorithm for Cardiologist-Level Arrhythmia Detection. The precision and recall occurred this method was better than the existing methods but this method required more memory. Serkan Kiranyaz *et al*. [38] developed a classification and monitoring model by using 1-D CNN. This method was used for any kind of dataset. The main disadvantage of this method was the difficulty in the hardware implementation. M.M. Al Rahhal *et al.* [39] proposed a method for ECG classification, which is based on deep learning. The main advantages of this method were faster online retraining, and less expert interaction. The accuracy of this method was not effective in certain expert iteration.
G. Sannino, and G. De Pietro [40] developed an ECG classification with deep learning approach. The accuracy of this method was high but it had difficulty in applying the real-world applications. Oliver Faust *et al.* [41]

developed a deep learning based method, which was applicable for big datasets. Anyhow, the quality of diagnosis was needed to be improved. U. Rajendra Acharya *et al.* [42] developed a CAD model for automatically detect the ECG signal segments, which was used to effectively diagnosis the arrhythmias. Small number of classes was used in this method. Özal Yildirim [43] implemented a model named as, deep bidirectional LSTM network-based wavelet sequences (DBLSTM-WS), which offered high recognition performance. This method had the problem with noise-added data. U. Rajendra Acharya *et al.* [44] implemented a model for arrhythmia diagnosis, which was used in both noise and noise-free ECGs. The main disadvantage of this method was the recognization of temporal sequence of ECG heartbeat signals. Moussa Amrani *et al.* [45] implemented a very deep convolutional neural network (VDCNN). The ECG signal processing of this method had better generalization ability, and learning performance. However, this method was applicable for detecting limited number of abnormal cases. Shu Lih Oh *et al.* [46] implemented a CAD model for arrhythmia diagnosis, which gave the accurate and timely results to the patients. The processing of variable strength signal was the challenging task of this method. Shu Lih Oh *et al.* [48], developed a model, which was the combination of convolutional neural network (CNN) and long short-term memory (LSTM) for the automatic diagnosis of various heart beats classification. The main advantage of this method was accuracy of the routine screening ECG. The limitation of this method was the identification of the variations of duration in short and long heart beat signals.

2.2 Challenges

The challenges of the research are demonstrated below:

- There are a number of challenges associated with the automatic classification of the heart beats. The first challenge is regarding the variability in the processes, such as pathos physiological and physiological that is associated with the tracing of the ECG signals among the patients, or for an individual over time. The second challenge is concerned with the stochastic ability of the afore-mentioned processes. The third challenge is due to the simultaneous presence of multiple physiological processes, which interacts in various ways. The fourth major challenge is regarding the noise and the artifacts present in the signal, which degrades the physiological functions. Finally, the lack of the accurate heart model drags the manual experience in effective decision-making [4].

- The major significant challenge to be addressed is the computationally-intensive nature of the classification methods of ECG [15]. Therefore, operating the devices using multiple resources proves their effectiveness. However, there are problems when one employs the resource-constrained devices. Thus, implementing the algorithms in devices that hold minimal battery, power of processing, and memory increases the unfeasible nature as a result of the excess energy consumption and running time that highly depends on the computational complexity of those algorithms. Moreover, it is peculiar to note that the application of adequate features with minimal computational complexity causes a good quality monitoring, while enabling the minimization of the energy consumed and time [6].
- In case of the time-domain analysis, there are various fiducial features employed for classification. However, there are few challenges associated with the ambiguities, such as changes in the standards for onset and offset detection of fiducial points in the ECG waves, impacts on the location of the fiducial points as a result of the noise, and uncertainty while computing the boundaries and peaks corresponding to the ECG signals. All these issues results in the high degree of failure [8].

- There is a requirement to learn and understand the technologies used for extracting the data features of the ECG signals from various aspects [4]–[17]. However, there is huge information-loss associated with the features that are designed manually as those features are duly based on the human knowledge rather than the data themselves. On the other hand, it is hectic to tune the multiple parameters manually due to the similar reason define-above. Therefore, it is well understood that the learning techniques contribute much towards enhancing the classification performance depending on the extracted features [18]–[25] [7].

3. Arrhythmia classification using proposed optimization-based deep convolutional neural networks

The arrhythmia classification is a significant research as WHO highlights the death-troll of persons with cardiac diseases to be around 17.3 million [29], which insist the conventional cardiac therapies to be useless. More importantly, the people with the cardiac problems are suffering a lot, requiring the need for an accurate classification strategy. The accurate classification is done using the deep CNN, which is optimally tuned using the proposed BaROA. The classification error reduces and thereby, enhancing the accurate detection and the arrhythmia classification using the proposed BA-ROA-deep CNN is depicted in figure 1. Initially, the wave intervals are determined from the ECG signal, which is essential to determine the abnormalities in the signal, symbolizing the presence or absence of arrhythmia. Along with the wave intervals, the gabor features and the wavelet features are derived in such a way that the gabor, wave, and interval features establish the feature vector. The feature vector is fed to the arrhythmia classification module in which the extracted features are employed for deciding the patient to be with arrhythmia or no arrhythmia. Thus, for arrhythmia classification, deep CNN is employed, which is trained using the proposed BaROA that is the integration of the MOBA in ROA. The proposed classifier performs the accurate arrhythmia classification using the features from the ECG signal of the individuals. From the block diagram, it is clear that there are two steps, such as feature extraction and arrhythmia classification for which initially, the ECG signals are recorded.

3.1 Employ the sensor nodes for recording the ECG signals

For the arrhythmia classification, the ECG signals of the patients are collected and let us assume that there are g number of patient records. Therefore, the ECG signals collected from the patients are represented as,

$$E = \{E_1, E_2, ..., E_l, ..., E_g\} \tag{1}$$

where, g indicates the total ECG signals. The dimension of the ECG signal corresponding to the l^{th} patient is denotedas, $[1 \times y]$.

3.2 An approach for the generation of the wave components of ECG:

The extraction of the wave interval features from ECG signal is brought out through the multi-resolution wavelet-based approach [29]. Accordingly, the individual ECG signal is subjected to the eight-level decomposition, which is represented as, $De[E_l]$ and the result of eight-level decomposition is the eight levels of wavelet. There are lower frequencies associated with the QRS complex and hence, higher degree of decomposition corresponds to the extraction of the lower frequencies from ECG. Thus, the eight level of decomposition is denoted as,

$$\lfloor s_1^l, s_2^l, \ldots, s_8^l \rfloor = De[E_l] \tag{2}$$

where, $s_1^l, s_2^l, \ldots, s_8^l$ corresponds to the eight wavelets acquired from the ECG signal. The wavelets are detected as shown below: the R-peak is identified at first through choosing the respective wavelet coefficients, and then, the Q and S points are chosen based on the five-point differentiation idea. At last, the wavelet coefficients corresponding to S and T points are found. Thus, it is clear that the eight-level decomposition provides both the higher and lower frequency components in which the first four are the higher and the remaining four are the lower frequency components.

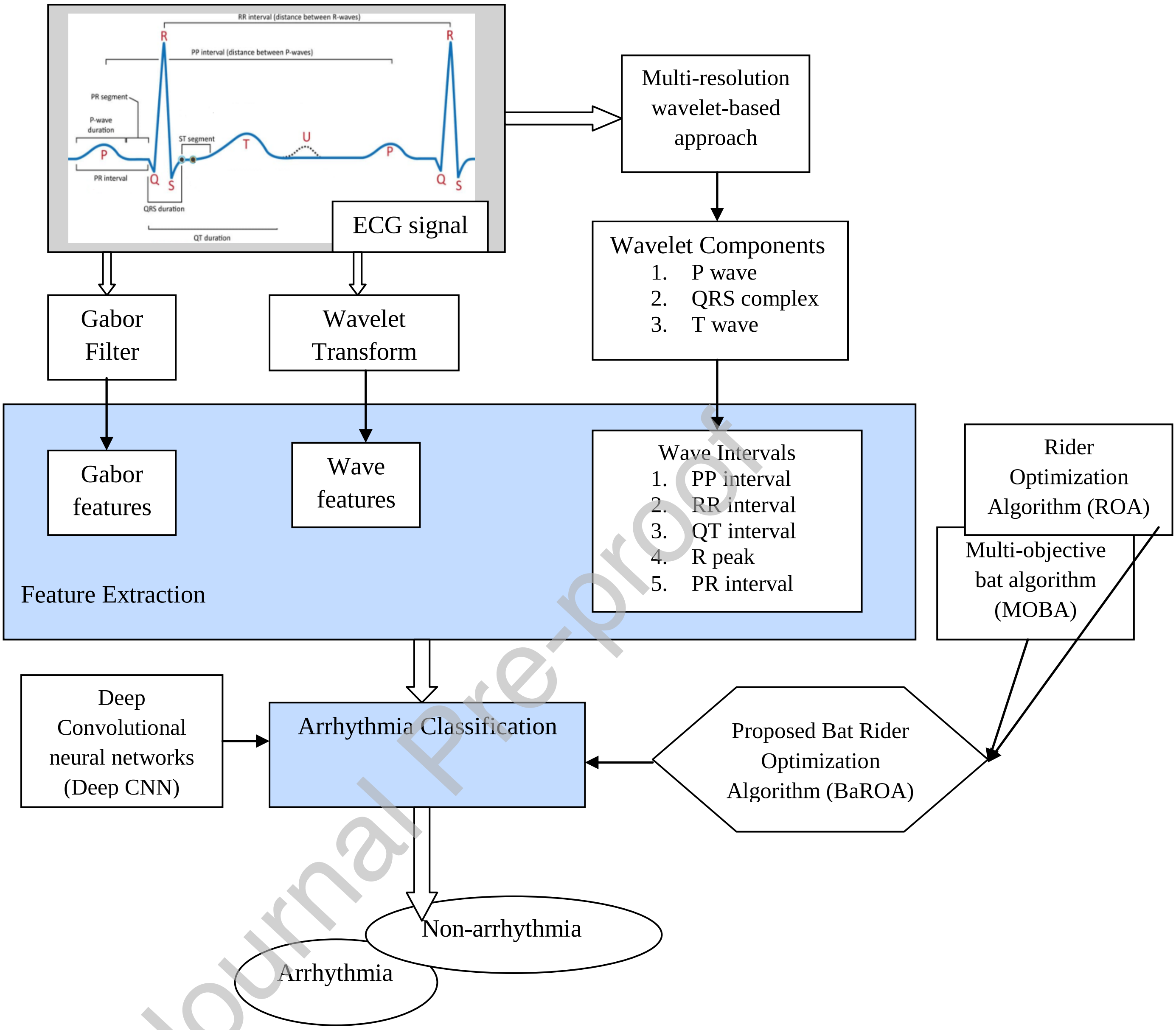


Figure 1. Block diagram of arrhythmia classification using BaROA-DeepCNN

3.2.1 R peak: The energy of QRS spectra reveals that the spectra energy with the three to fifth components corresponds to QRS since the other levels seems to be noisy at the time of detection. The reconstructed wave is given as,

$$w_1^l = s_3^l + s_4^l + s_5^l \tag{3}$$

The R peak is computed using the following equation,

$$w_2^l = \frac{s_4^l \times \left(s_3^l + s_5^l\right)}{2^u} \tag{4}$$

where, u specifies the decomposition degree and let us assume u to be 8. Thus, the modulus of first and second reconstructed waves, $\left|w_1^l \times w_2^l\right|$ is computed and the wave corresponding to the maximal amplitude is retrieved to represent the R peak of the ECG. The R-peak is determined accurately in order to make the effective features, which are essential for arrhythmia classification. In order to render the effective feature extraction, the selective coefficient-based approach is employed that assure the optimal wave coefficient selection based on the power spectrum of the wave.

3.2.2 Identification of the waves, S and Q: After the identification of the R-peak, the detection of the complete QRS complex is processed, where Q and S are the high-frequency components, while R is a low-frequency component. The wave reconstruction is represented as,

$$w_3^l = s_2^l + s_3^l + s_4^l + s_5^l \tag{5}$$

The five-point differentiation is appliedon the above equation for eradicating the noise with high-frequency. Thus, the equation becomes,

$$b^{'}(z) = \frac{-b(z+2q)+8b(z+q)-8b(z-q)+b(z-2q)}{12q} \tag{6}$$

The time division is represented as, q .Now, differentiate equation (5) with respect to equation (6) from which the first and second zero slope points available on both terminals of R peak represent the waves, S and Q.

3.2.3 Retrieving the waves, T and P: The reconstruction coefficients corresponding to level-6 and level-7 are used to detect the T and P waves since the corresponding energies fell under the final three scales. The wave, which is reconstructed, is given by,

$$w_4^l = s_6^l + s_7^l \tag{7}$$

The maximal point very next to S wave is the T wave and the crossing points possessing the minimum potential is considered as the T-offset and onset points. However, during cardiac arrest, the detection of T-waves is a hectic challenge and it is essential to note the shape of T-wave prior to feature extraction, which indicates that the nature of the T-wave is identified based on the sign of T-wave in a particular interval. Thus, after the identification of the individual waves, the interval is determined, which forms the feature vector.

3.3Developing the feature matrix

The feature matrix of an ECG is established based on the wave features and gabor features, which are presented as follows:

3.3.1 Extraction of the wave features: The wave features include the wave intervals, such as PP, RR, PR, QT, and R peak, which are presented as follows:

*a) PP interval:*The time interval between the two successive P-waves in the ECG is presented as PP interval. Consider that there are x number of points in a wave, which is represented as,

$$PP = \{PP_k \quad ;1 \le k \le x \tag{8}$$

$$PP^l = \frac{1}{x}\sum_{k=1}^{x}\left[P_l^k - P_l^{k+1}\right] \tag{9}$$

where, P_l^k denotes the PP component of l^{th} patient. The PP interval of all the x points is averaged to form the PP feature.

b) PR interval: The time interval between the P and R wave corresponding to the k^{th} point is computed to determine the PR interval. Finally, the mean of the PR interval of all points are summed to form the PR feature of the ECG signal.

$$PR = \{PR_k \quad ;1 \le k \le x \tag{10}$$

$$PR^l = \frac{1}{x}\sum_{k=1}^{x}\left[P_l^k - R_l^{k+1}\right] \tag{11}$$

c) RR interval: The time interval between the successive R waves is represented as, RR interval, which is given as,

$$RR = \{RR_k \quad ;1 \le k \le x \tag{12}$$

$$RR^l = \frac{1}{x}\sum_{k=1}^{x}\left[R_l^k - R_l^{k+1}\right] \tag{13}$$

*iv) QT interval:*The time interval between the ECG waves Q and T intervals is known as QT interval, which is denoted as,

$$QT = \{QT_k \quad ;1 \le k \le x \tag{14}$$

$$QT^l = \frac{1}{x}\sum_{k=1}^{x}\left[Q_l^k - T_l^{k+1}\right] \tag{15}$$

*v) R peak:*The R peak feature is computed through averaging the maximal amplitude of the ECG signals as given by,

$$R^l = \frac{1}{x}\sum_{k=1}^{x} R^k \tag{16}$$

Thus, the features extracted from the l^{th} patient is given as,

$$F_l^{\text{int}} = \left\{PP^l, PR^l, RR^l, QT^l, R^l\right\} \tag{17}$$

where, F_l indicates the feature vector of l^{th} patient and the dimension is given as, $[1\times 5]$.

3.3.2 Gabor filter for extraction of the gabor features: The gabor filter is applied to the ECG signal for extracting the gabor features, like variance, skewness, mean, standard deviation, entropy, energy, and kurtosis. The band-pass filter or gabor filter acquires the texture features and the benefit of using the gabor filter is regarding their ability to detect the optimal properties of the signal, which represent the texture featuers both in the spatial as well as in the time domain. Additionally, these filters are capable of dealing with the uncertainties in the spatial and time domain. The gabor features are represented as,

$$F_l^{gab} = \left\{\mu^l, \upsilon^l, e^l, X^l, \sigma^l, \zeta^l, \kappa^l\right\} \tag{18}$$

w*here,* μ^l, $\upsilon^l, e^l, X^l, \sigma^l, \zeta^l, \kappa^l$ are the mean, variance, energy, entropy, standard deviation, skewness, and kurtosis of the l^{th} ECG signal. Thus, the feature vector is represented as,

$$F_l = \left\{F_l^{\text{int}}, F_l^{gab}\right\} \tag{19}$$

The dimension of the feature vector is, $[1\times 12]$, which symbolizes that for the g number of ECG samples, the dimension of the feature vector is, $[g \times 12]$.

3.4 Proposed BaROA-based DCNN classifier for the effective and optimal classification of the arrhythmia using the ECG features

Using the features determined from the ECG signal, the arrhythmia classification is progressed for which the deep CNN classifier is employed. In this section, the proposed BaROA-is described with the clear view over the optimization steps. The ultimate goal of BaROA is to determine the optimal weights for tuning the DCNN classifier for classifying arrhythmia.

3.4.1 Solution Encoding: The goal of solution encoding is to present the solution to be derived using the proposed BaROA optimization. The solution vector is of dimension, $[1\times \mathrm{N}]$ where, N corresponds to the total number of weights to be computed using the proposed optimization.

3.4.2 Fitness Function: The optimal weights are determined using the fitness measure, which is computed based on the error value of the classifier. The error of the classifier is computed as the difference between the estimated output and the target output of the classifier, which is given as,

$$Er = \frac{1}{g}\left[O_{est} - O_{tar}\right]^2 \tag{20}$$

where, O_{est} is computed as the output of the classifier and O_{tar} corresponds to the target output.

3.4.3 Arrhythmia Classification using the BaROA-based DCNN classifier

The arrhythmia classification is progressed using theBaROA-based DCNN classifier, which is the integration of the proposed BaROA in the deep CNN classifier. The proposed algorithm aim at determining the optimal weights of the classifier and BaROA is the integration of the standard MOBA [27] in the update rule of ROA [28]. The significance of the classifier is that the classification accuracy of the classifier is high due to the compact features acquired from the ECG signal.

a) Structure of the Deep CNN: The features are fed as input to the Deep CNN, which performs the arrhythmia classification. In deep CNN, there are three layers, such as convolutional (conv) layers, pooling (POOL) layer, and Fully Connected (FC) layer. The deep CNN differs from the normal NN in structure, where a single neuron is connected to the other, while in deep CNN, a patch of the neurons are connected with the neurons in the successive layers. The individual layers in deep CNN perform their own task of acquiring the confine features, sub-sampling, and classification. Figure 2 shows the architecture of deep CNN.

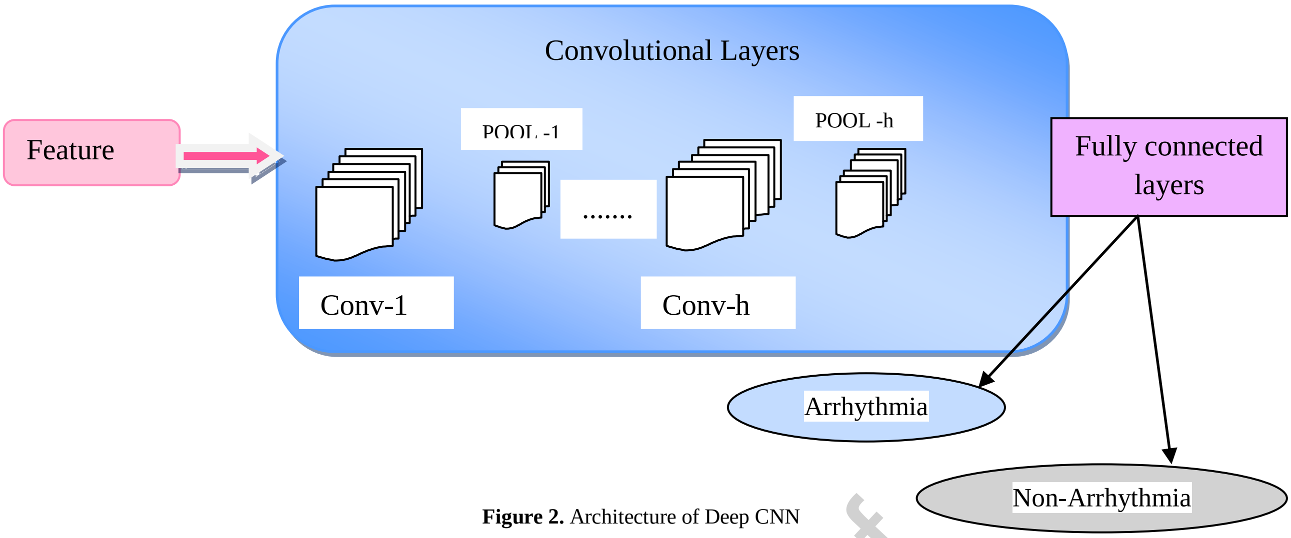


Figure 2. Architecture of Deep CNN

Conv layers: The function of conv layer is to acquire the confine features buried in the input feature vector for which the conv filters are applied to the input. The input features are carried to the next layer through the receptive fields and the link to the successive layers are enabled with a set of the trainable weights. The function of conv layer is associated with the convolutional operator using which the input data is convoluted with the kernel filter and weights, which are determined optimally using BaROA. Thus, at the output of each set of the layers, a set of confine features are derived, which are fed as input to the successive layers of conv units. Let us assume that there are h number of conv layers in the deep CNN and it is worth to note that the number of the convolutional layers is associated with the accuracy of classification. The accuracy is directly proportional to the total number of the convolutional layers in the deep CNN classifier. Thus, the output from the a^{th} convolutional layer is given by,

$$\left(c_f^a\right)_{P,Q} = \left(B_f^a\right)_{P,Q} + \sum_{d_1=1}^{v_1^{d_1-1}} \sum_{d_2=-v_1^a}^{v_1^a} \sum_{d_3=-v_2^a}^{\kappa_2^a} \left(\chi_{f,d_1}^a\right)_{\upsilon,\tau} * \left(c_{d_1}^{a-1}\right)_{P+d_2,Q+d_3} \tag{21}$$

where, $*$ represents the convolutional operator. The conv layer a extracts the local patterns, from the input of the previous conv layer. $\left(c_f^a\right)_{P,Q}$ is the fixed feature map and it marks the output from a^{th} conv layer that is located at, (P,Q). It is peculiar to note that the output from the previous $(a-1)^{th}$ conv layer is the input to a^{th} conv layer. Let us represent the weights of the conv layers that is denoted as, χ_{f,d_1}^a, which represent the weights of a^{th} conv layer and let us indicate the bias of a^{th} conv layer as, B_f^a. Consider that there are h number of conv layers and the notations, such as d_1, d_2, and d_3 denote the feature maps, and feature maps are the output obtained from the individual conv layers through applying the conv filter to the input feature vector. Moreover, the neurons available in the conv layers are organized in 3-dimensions along its width, height, and depth in order to extract the features at all the dimensions. The output from the conv layer is fed to the ReLU layer and the output of the ReLU layer is given as, ,

$$c_f^a = fn\left(c_f^{a-1}\right) \tag{22}$$

The speed of deep CNN to extract the confine features for classification is of greater significance and ReLU layer extends the ability to deal with huge number of the layers in the classifier.

POOL layers: The non-parametric layer without any bias or weight is the POOL layer that is said to possess the stable operation.

Fully connected layers: In the FC layer, the classification is carried for which the confined features are acquired from the features using the conv layers. Finally, the classification at FC layer enables the classification of the features to declare the patients with arrhythmia or no arrhythmia. The output of FC layer is denoted as,

$$\left(c_f^a\right) = \delta\, c_f^a \quad with \sum_{d_1=1}^{v_1^{d_1-1}} \sum_{d_2=-v_1^a}^{v_1^a} \sum_{d_3=-v_2^a}^{\kappa_2^a} \left(\chi_{f,d_1}^a\right)_{\upsilon,\tau} * \left(c_{d_1}^{a-1}\right)_{P+d_2,Q+d_3} \tag{23}$$

However, the accurate classification of the arrhythmia patients is based on the weights and the biases employed in the classifier and these weights and biases are determined using the proposed BaROA.

b) Proposed BaROA Optimization algorithm: The proposed BaROA algorithm is the integration of the MOBA in the ROA in such a way that the update rule of bypass rider is modified using the update equation of ROA. The proposed BaROA balances the merits and demerits of MOBA and ROA and more importantly, the proposed algorithm renders a higher convergence rate with a global optimal solution and higher tendency towards the local optimal avoidance mechanism. On the other hand, the diversity of the solutions is assured with a better convergence rates and the capacity of BaROA to deal with the multiple objectives is effective.
In general, ROA operates based on the imaginary ideas and thoughts, which uses a new environment named, fictional computing, which is a unique computing platform, as like the artificial computing and nature-inspired platforms. ROA is based on the optimization characteristics of the riders, where there are four groups of riders, such as bypass, over taker, attacker, and follower. Each of the riders exhibits their own characteristics and all riders aim towards the destination. The best rider is decided based on the factor, termed as success rate, which should be maximal for the best rider or leading rider. Moreover, it is worthy to note that ROA is the only optimization, operating under the fictional concept. The major significance of ROA is that the global optimal solution is rendered, which is nothing but the weights and biases of the classifier. Moreover, based on the leading rider, the position of the other four group of riders update their positions and the factors essential for updating the positions include: the steering angle, accelerator, gear, and so on. The riders update their positions based on the position of the leader and moreover, the optimization keeps away from the local minimal avoidance to the small local neighbourhood. This ability of the local optimal avoidance is brought about by the attacker. On the other hand, ROA possess higher convergence rate, which depends on the large global neighbors and the convergence mechanism is the effort of the over taker. Thus, the positions are randomly updated initially for exploring the surroundings. The over taker acquires the optimal search space for which the success rate and directional indicator are the major factors, while the follower uses the multi-dimensional space corresponding to the leading rider. It is peculiar to note that the searching speed of the attacker is accelerated as the results of the multidimensional search. Moreover, ROA renders effective search-ability. However, the ability to handle the multi-objective function is a major question for which the MOBA plays a major role. Thus, integrating the MOBA with ROA offers effective multi-objective handling ability. MOBA is duly based on the echolocation of the bats in detecting the prey. Following is the algorithmic steps of the proposed BaROA:

i) Initialization*:* As mentioned earlier, there are four groups of riders namely, bypass, overtaker, attacker, and follower, which are initialized as, P_1, P_2, P_3, and P_4, respectively. According to the rider groups, there are unique features for each group. The bypass rider takes a new path other than the common path, while the follower follows the leader. On the other hand, the over taker overtakes other riders, and the attacker attacks the leader with the aim to win over the leader. However, the aforementioned characteristics of the riders are acquired as a result of the adjustment done on the vehicle parameters. The riding parameters of i^{th} rider include: coordinate angle, steering angle, and position angle that are represented as, $C_{i,j}(t)$, $S_{i,j}(t)$ and $K_{i,j}(t)$. Likewise, the accelerator, gear, and brake of i^{th} rider is denoted as, ω_i, G_i, and β_i, respectively. The gear G_i takes a value between 0 and 4, while the accelerator and gear takes a value ranging between 0 and 1.
The search-space consists of m number of riders and they are represented as,

$$P_{i,j}^{t+1};(1 \le i \le m);(1 \le j \le r) \tag{24}$$

where, r refers to the total coordinates in the search-space. $P_{i,j}^{t+1}$ notate the position of the i^{th} rider in j^{th} dimensional space at time $(t+1)$.

ii)Compute the success rate: The success rate is a factor that finalizes the leading rider. Accordingly, the success rate with the maximal value is declared as the leading riderand in this paper, the success rate is denoted as, sr, which is nothing but the MSE given in equation (20). It is peculiar to note that the leading rider leads the race and he is the one nearer to the destination and on the other hand, a leading rider is not always supposed to lead the race instead the leading rider changes. Thus, the success rate is evaluated at the end of every iteration.

iii)Position update phase:The rider groups update their position based on the position of the leading rider as follows: The position of the bypass rider is updated as follows:

$$P_{i,j}^{t+1}(R_1) = \alpha\left[P_{j,\varepsilon}^{t} * \delta(j) + P_{j,\lambda}^{t} * (1-\delta(j))\right] \tag{25}$$

where, δ and α are the random numbers varying between 0 and 1, λ and ε specifies the random numbers varying between 1 and m. The dimension of δ is given as, $[1 \times r]$. $P_{i,j}^{t+1}(R_1)$ is the position of the bypass rider at the next instant and $P_{j,\varepsilon}^{t}$ is the position of the bypass rider at present. The update equation of the bypass rider is modified using MOBA to inherit the proposed BaROA for which the update equation of MOBA is interpreted. The proposed algorithm ensures better search-ability and diversity and in addition, the global optimal convergence is rendered. The standard equation of MOBA is given as,

$$P_{i,j}^{t+1} = P_{i,j}^{t} + v_{i,j}^{t} + \left(P_{i,j}^{t} - P_{best}\right)\gamma_{i,j} \tag{26}$$

The above equation is rearranged and rewritten as,

$$P_{i,j}^{t+1} = P_{i,j}^{t} + v_{i,j}^{t} + P_{i,j}^{t} \times \gamma_{i,j} - P_{best} \times \gamma_{i,j} \tag{27}$$

$$P_{i,j}^{t} = \frac{1}{1+\gamma_{i,j}}\left[P_{i,j}^{t+1} - v_{i,j}^{t} + P_{best} \times \gamma_{i,j}\right] \tag{28}$$

Substitute the equation (28) in equation (25) for which we consider the assumption $\varepsilon = i$ in equation (25). Thus, we get,

$$P_{i,j}^{t+1}(R_1) = \alpha\left[\frac{\delta(j)}{1+\gamma_{i,j}}\left[P_{i,j}^{t+1} - v_{i,j}^{t} + P_{best} \times \gamma_{i,j}\right] + P_{j,\lambda}^{t} * (1-\delta(j))\right] \tag{29}$$

$$P_{i,j}^{t+1}(R_1) - \frac{\alpha \times \delta(j)}{1+\gamma_{i,j}} \times P_{i,j}^{t+1} = \alpha\left[\frac{\delta(j)}{1+\gamma_{i,j}}\left[-v_{i,j}^{t} + P_{best} \times \gamma_{i,j}\right] + P_{j,\lambda}^{t} * (1-\delta(j))\right] \tag{30}$$

$$P_{i,j}^{t+1}(R_1)\left[1 - \frac{\alpha \times \delta(j)}{1+\gamma_{i,j}}\right] = \alpha\left[\frac{\delta(j)}{1+\gamma_{i,j}}\left[-v_{i,j}^{t} + P_{best} \times \gamma_{i,j}\right] + P_{j,\lambda}^{t} * (1-\delta(j))\right] \tag{31}$$

$$P_{i,j}^{t+1}(R_1) = \left[\frac{1+\gamma_{i,j}}{1+\gamma_{i,j} - \alpha\delta(j)}\right]\left\{\alpha\left[\frac{\delta(j)}{1+\gamma_{i,j}}\left[-v_{i,j}^{t} + P_{best} \times \gamma_{i,j}\right] + P_{j,\lambda}^{t} * (1-\delta(j))\right]\right\} \tag{32}$$

Thus, equation (32) is the update equation of BaROA, which differs from the standard ROA as there are additional optimization factors, like velocity $v_{i,j}^{t}$ and the global best solution of the previous iteration, P_{best}. The additional optimization parameters further enhances the convergence rate and assures global optimal solution. The second group of riders, follower updates their position based on the following equation,

$$P_{i,\ell}^{t+1}(R_2) = L_{V,\ell} + \left[\cos(S_{i,\ell}(t)) * L_{V,\ell} * Y_i(t)\right] \tag{33}$$

Let $L_{V,\ell}$ is the position of the leader, L refers to the leading rider, $P_{i,j}^{t+1}(R_2)$ is the position of the follower, and $Y_i(t)$ is the distance traveled by k^{th} rider at instant t. The distance $Y_i(t)$ is measured based on the velocity and off-time and the velocity of i^{th} rider depends on the maximum speed, accelerator, gear, and brake with respect to the vehicle of i^{th} rider. The selection of the co-ordinate selector depends on the on-time probability. On the other hand, the over taker updates the position using the direction indicator, coordinate selector, and success rate. The position of over taker is given as,

$$P_{i,\ell}^{t+1}(R_3) = P_{i,\ell}^{t}(t) + \partial_i(t) * L_{V,\ell} \tag{34}$$

where, $P_{i,\ell}^{t}(t)$ is the position of i^{th} rider in ℓ^{th} coordinate and $\partial_i(t)$ is the direction indicator corresponding to i^{th} rider at time t. The direction indicator $\partial_k(t)$ is computed based on the success rate and hence, the formula,

$$\partial_i(t) = \left[\frac{2}{1-\log(SR)}\right] - 1 \tag{35}$$

The position of the attacker and follower are similar and hence, the position of the attacker is updated as,

$$P_{i,\ell}^{t+1}(R_4) = L_{V,\ell} + \left[\cos(S_{i,\ell}(t))\right] * L_{V,\ell} + Y_i(t) \tag{36}$$

iv) Re-evaluate the success rate: The success rate of the riders is recomputed every-time after the rider groups update their positions to signify that the leader is not always the same rider.

v) Update the parameters of the rider: Once the success rate is re-evaluated, the optimization parameters, like the vehicles parameters of the rider, gear, steering angle, accelerator, brake, off-time, and activity counter are updated.

vii)End:The steps are repeated until the destination is met by any of the rider groups, marking the announcement of the winner. Algorithm 1 shows the pseudocode of the proposed BaROA algorithm.

Algorithm 1. BaROA- Pseudo code

BaROA algorithm
Input : Rider's position $P_{i,\ell}^{t+1}$
Output : Leading rider $L_{V,\ell}$
Start
Initialization
Rider population and riding parameters
Position angle $K_{i,j}(t)$
Steering angle $S_{i,j}(t)$
Accelerator ω_i
Gear G_i
Coordinate angle $C_{i,j}(t)$
Brake β_i
Compute the success rate
While $t < t_{off}$
For $(i = 1 \; to \; m)$
#Position update phase
eqn. (32) for updating the bypass riders' position
Followers' position using eqn. (33)
Overtakers' position using eqn. (34)
Follow eqn. (36) for attacker position update
Ranking the riders with respect to the success rate
Determine the leading rider
Update the Rider parameters
Return $L_{V,\ell}$
$t = t + 1$
End For
End While
Terminate

4. Results

The outcome of arrhythmia classification using the proposed BaROA-DCNN is depicted with respect to the existing methods to reveal the effective arrhythmia classification method.

4.1 Database used

The MIT-BIH Arrhythmia Database [30] is considered for the experimentation and this database is collected from the Boston's Beth Israel Hospital. The ECG from 47 individuals from the due year 1975-1979 is collected and digitized at 360 samples per second in a channel such that it carries a 11-bit resolution in the entire10 mV range.

4.2 Evaluation metrics

The metrics used for analyzing the performance of the methods are described in this section as shown below:

*4.2.1*Accuracy is the degree of accurateness and is computed as,

$$Accuracy = \frac{T_1 + T_2}{T_1 + T_2 + N_1 + N_2} \tag{37}$$

where, T_2 is true positive, N_1 is false negative, T_1 is true negative, and N_2 is false positive.

4.2.2 Sensitivity is the degree of true positives, which is measured as,

$$Sensitivity = \frac{T_2}{T_2 + N_1} \tag{38}$$

*4.2.3*Specificity is the measure of true negatives and is computed as,

$$Specificity = \frac{T_1}{T_1 + N_2} \tag{39}$$

4.3 Experimental analysis

The section demonstrates the sample results of the experiment for which two ECG signals are considered. The ECG signals and the arrhythmia-affected signals are depicted in this section. Figures 3-8 show the experimental results corresponding to the original and affected ECG signals of signal-1, signal-2, and signal-3. The waves of the ECG signal corresponding to the normal ECG original signal_1 is depicted in figures 3 a)-3 f), respectively. The corresponding arrhythmia-affected signal is depicted in figure 4 a) – 4 f). The normal signal-2 and signal-3 are shown in figures 5 a)- 5 f) and 7 a)- f), respectively. Similarly, the arrhythmia-affected signals of the considered signals, signal_2 and signal_3 are depicted in figures 6 a)-f) and 8 a)-f), respectively. The deviations between the original signals and the arrhythmia-affected signals are addressed in the intervals, which vary between the normal and affected signals. The time intervals between the P, Q, R, S, and T may be long or less when compared with the normal signals to report the abnormality.

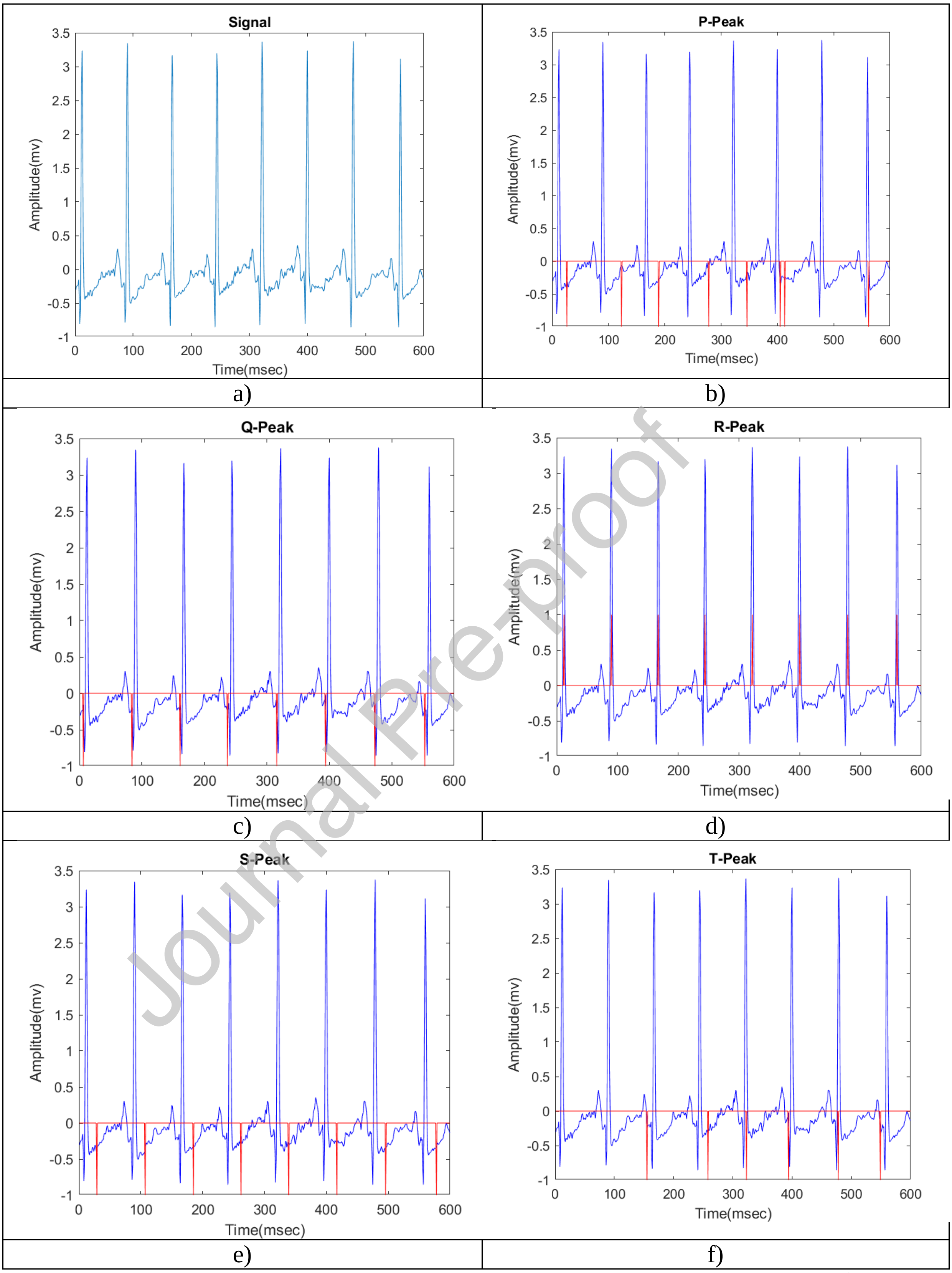


Figure 3. Experimental analysis using normal signal-1, a) Original signal_1, b) P-Peak, c) Q-peak, d) R-Peak, e) S-Peak, f) T-peak

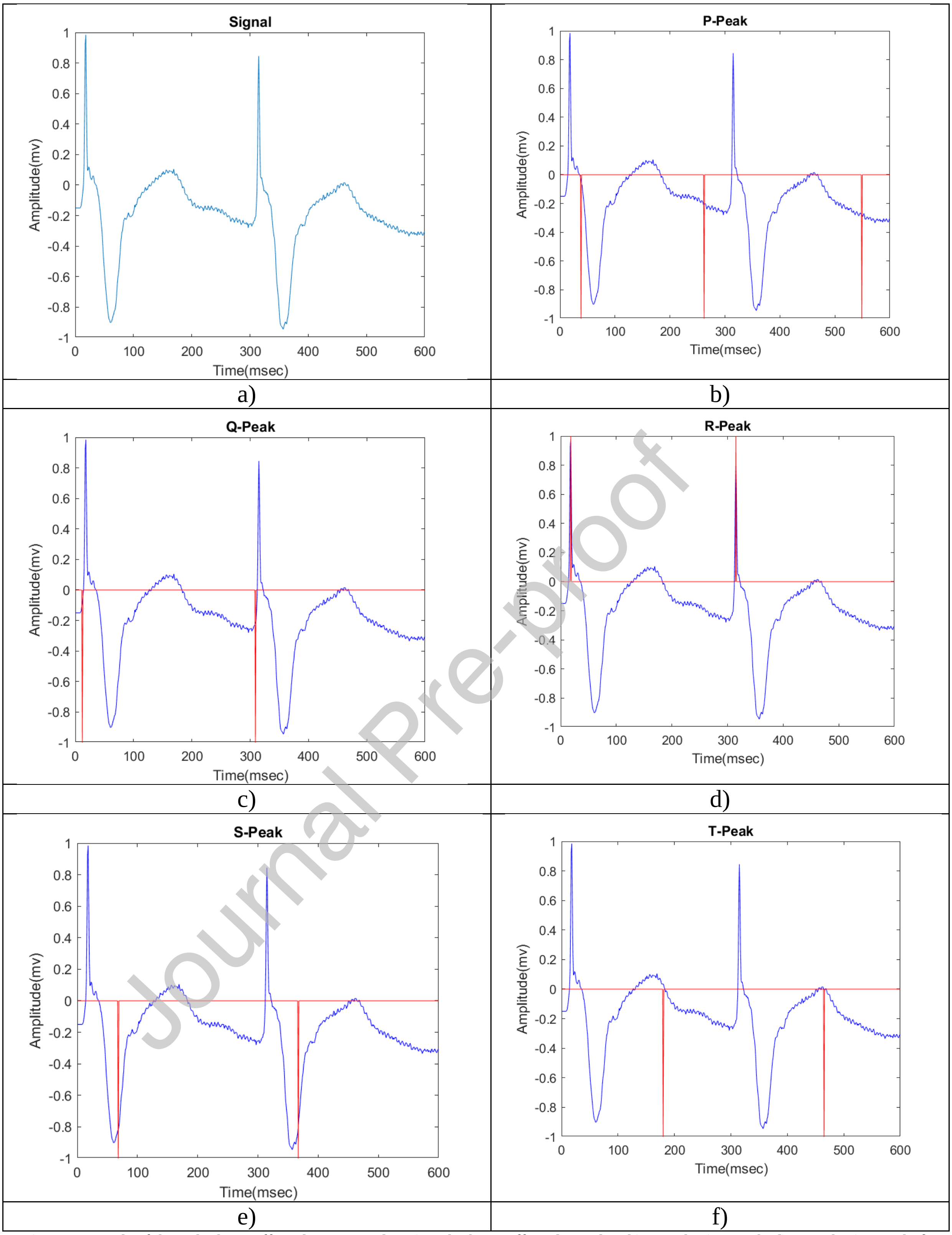


Figure 4. Signals of the arrhythmia affected ECG signal-1, a) Arrhythmia-affected signal_1, b) P-Peak, c) Q-peak, d) R-Peak, e) S-Peak, f) T-peak

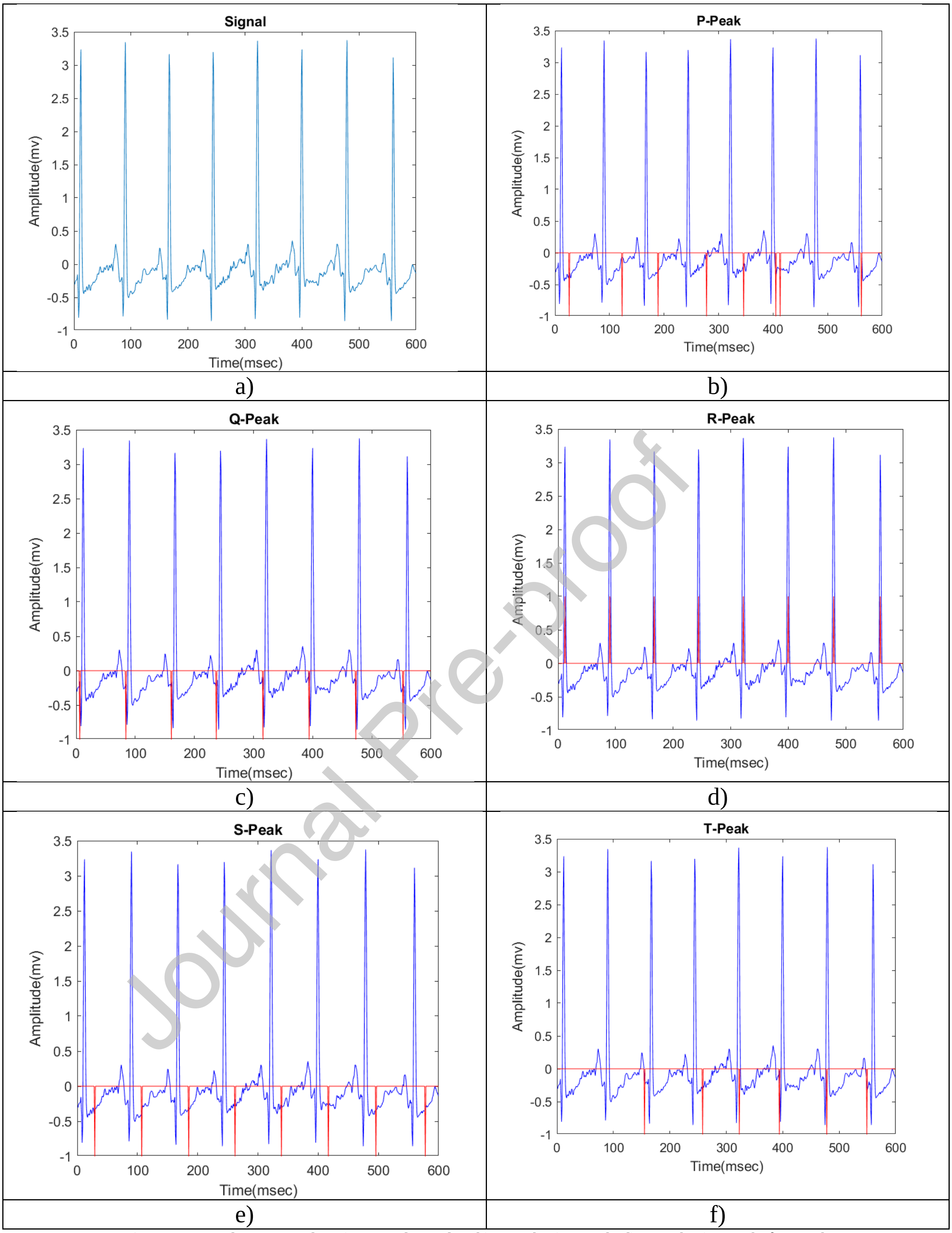


Figure 5. Normal ECG signal-2, a) Original signal_2, b) P-Peak, c) Q-peak, d) R-Peak, e) S-Peak, f) T-peak

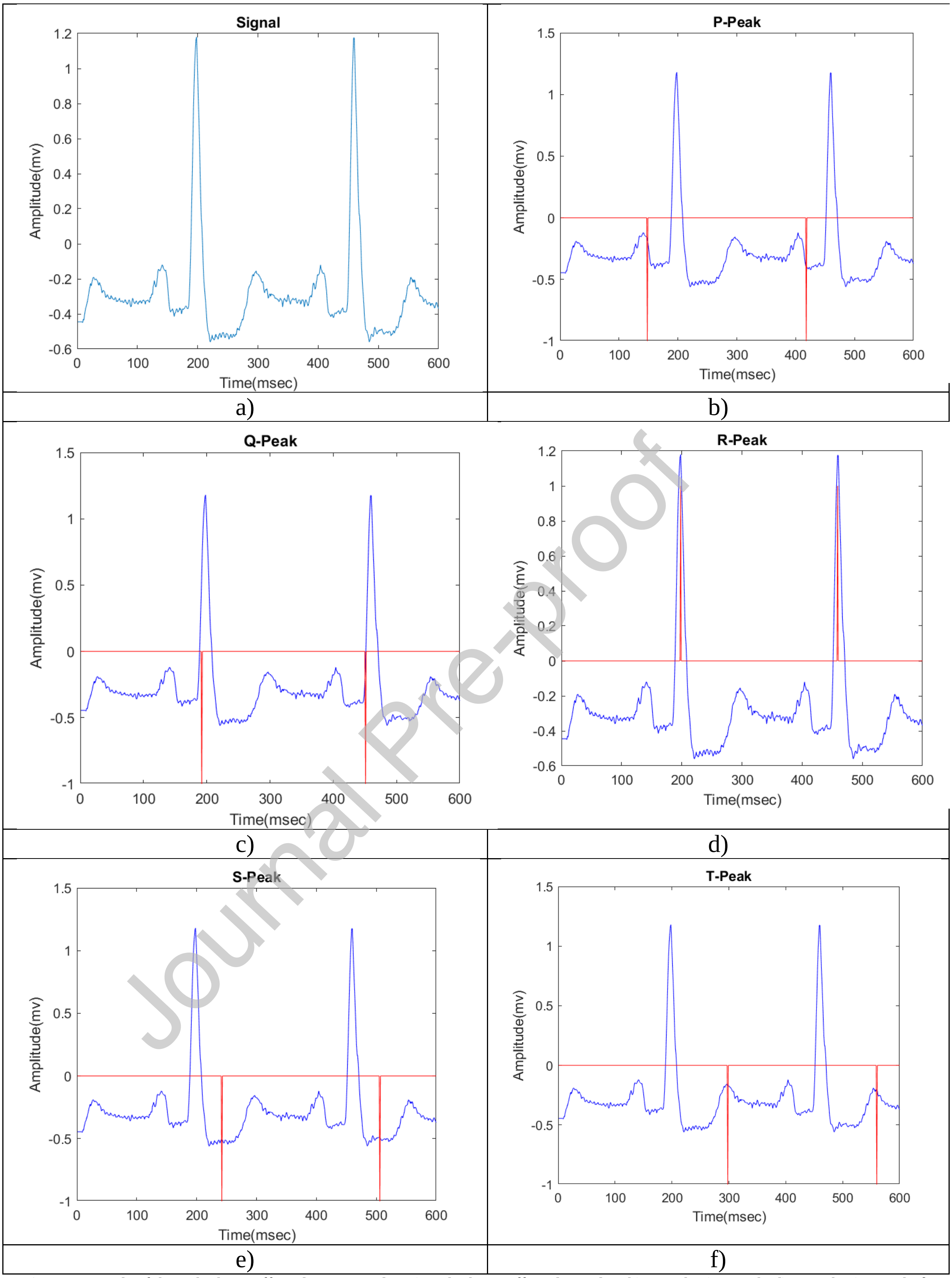


Figure 6. Signals of the arrhythmia affected ECG signal-2, a) Arrhythmia-affected signal_2, b) P-Peak, c) Q-peak, d) R-Peak, e) S-Peak, f) T-peak

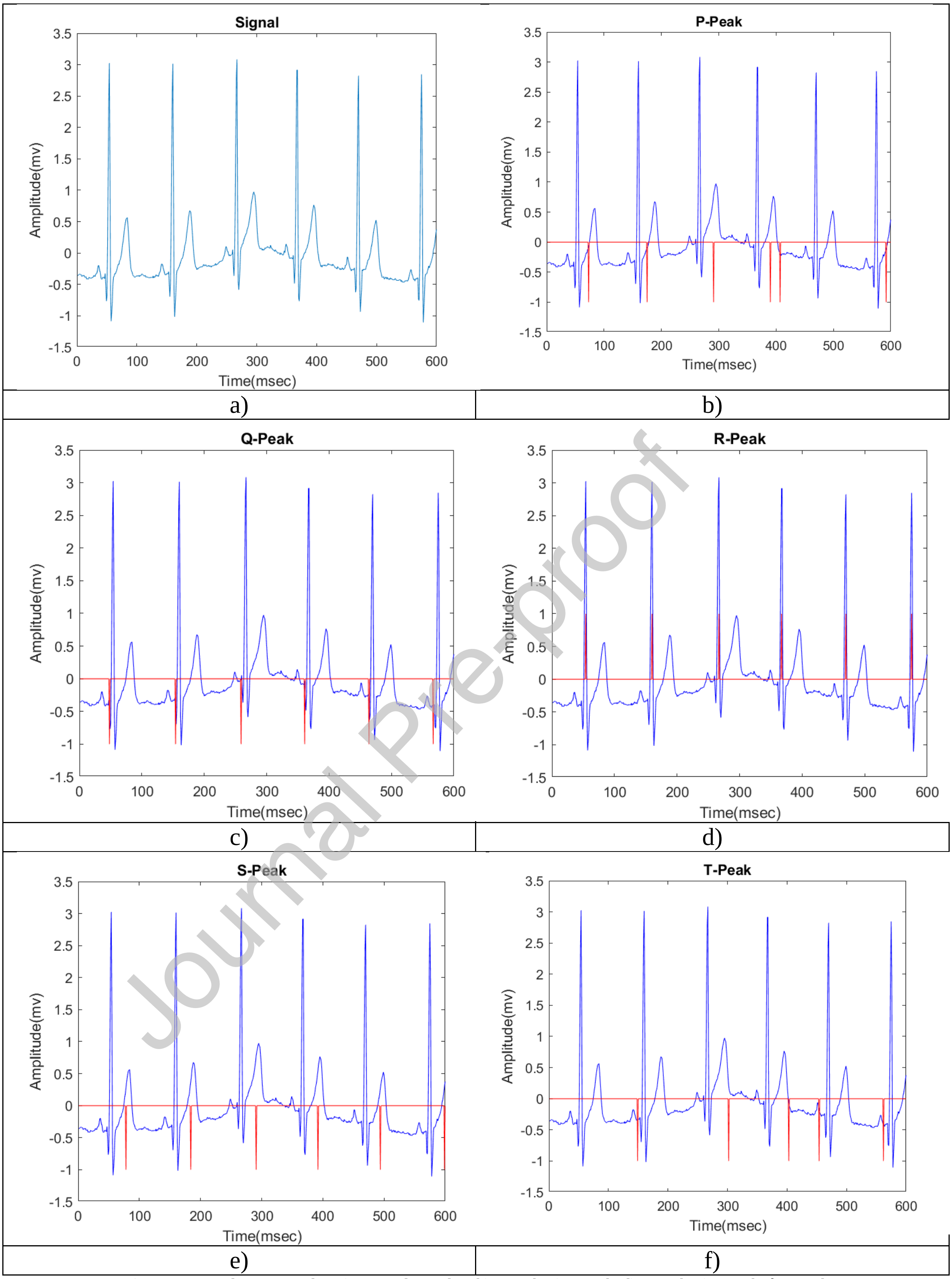


Figure 7. Normal ECG signal-3, a) Original signal_3, b) P-Peak, c) Q-peak, d) R-Peak, e) S-Peak, f) T-peak

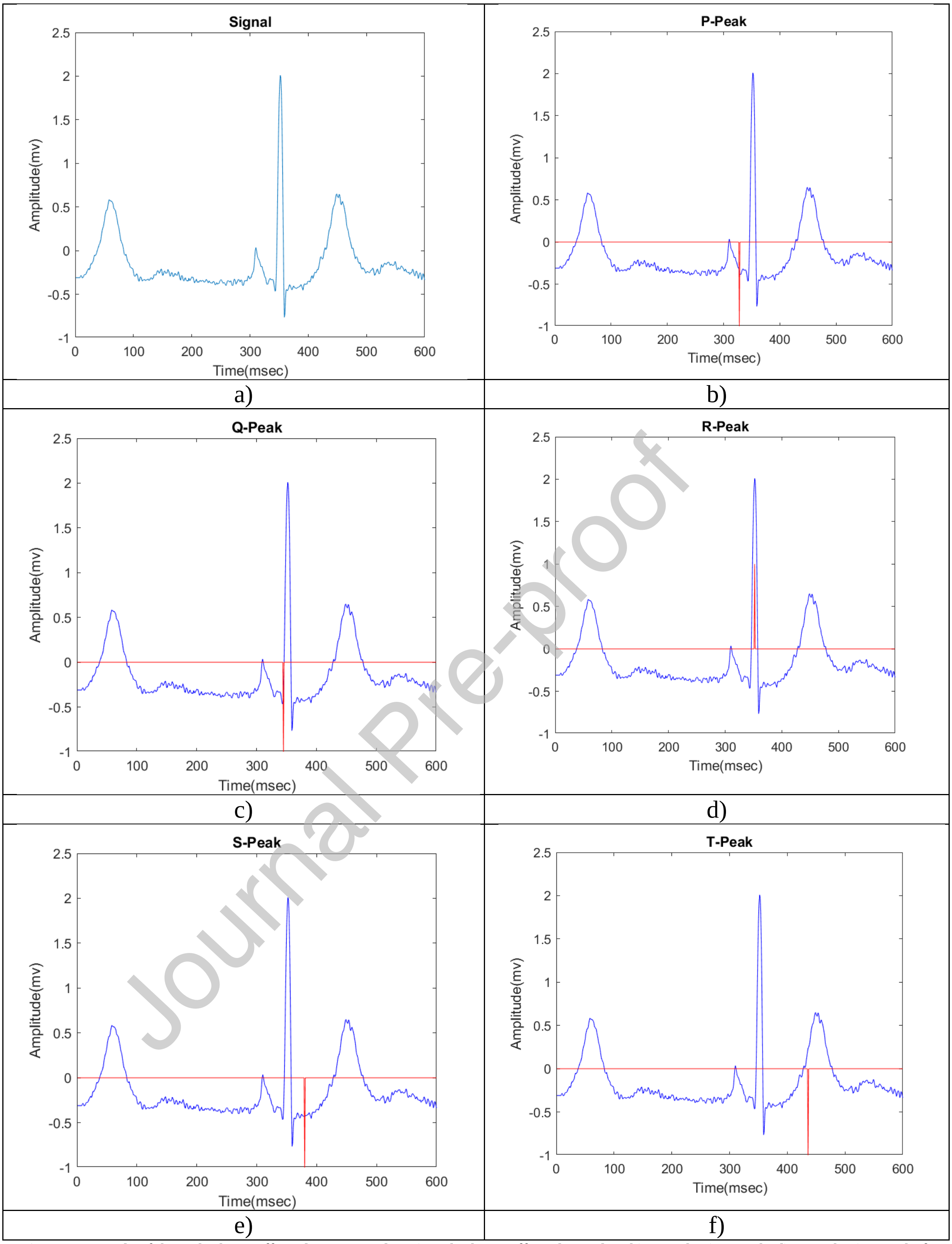
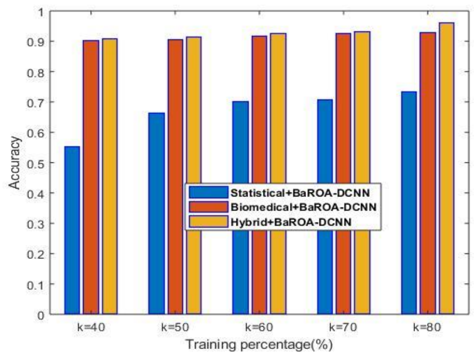


Figure 8. Signals of the arrhythmia affected ECG signal-3, a) Arrhythmia-affected signal_3, b) P-Peak, c) Q-peak, d) R-Peak, e) S-Peak, f) T-peak

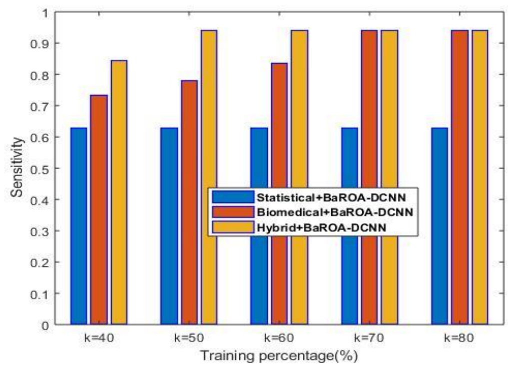
4.4 Performance analysis

Figure 9 depicts the comparative analysis using ECG signal_1. Figure 9 a) shows the analysis based on the accuracy. When the percentage of training data is 40, the accuracy of statistical + BaROA-DCNN, Biomedical+ BaROA-DCNN, and hybrid-BaROA-DCNN is 0.5531, 0.9009, and 0.9083, respectively.Figure 9 b) shows the analysis based on the sensitivity. When the data percentage is 40, the sensitivity of the methods, statistical +

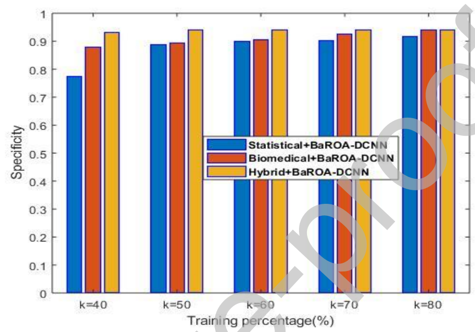
BaROA-DCNN, Biomedical+ BaROA-DCNN, and hybrid-BaROA-DCNN is 0.6292, 0.7320, and 0.8434, respectively. Figure 9 c) shows the analysis based on the specificity. When the training percentage is 40, the specificity ofstatistical + BaROA-DCNN, Biomedical+ BaROA-DCNN, and hybrid-BaROA-DCNN is 0.7744, 0.8784, and 0.9322, respectively.



a)



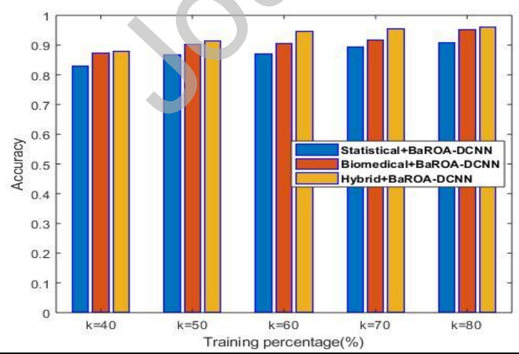
b)



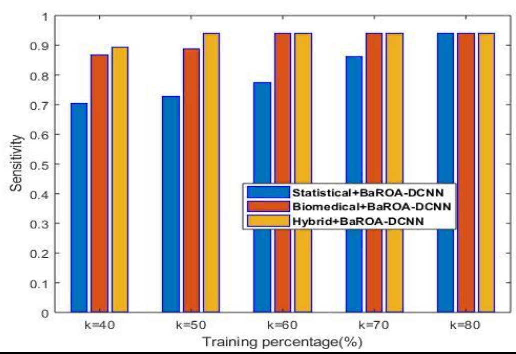
c)

Figure 9. Performance analysis using 50 convolutional layers with iteration count as 250, a) accuracy, b) sensitivity, c) specificity

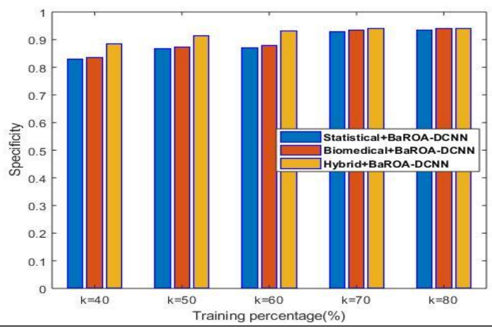
Figure 10 depicts the comparative analysis using ECG signal_2. Figure 10 a) shows the analysis based on the accuracy. When the percentage of training data is 40, the accuracy of statistical + BaROA-DCNN, Biomedical+ BaROA-DCNN, and hybrid-BaROA-DCNN is 0.8297, 0.8733, and 0.8804, respectively. Figure 10 b) shows the analysis based on the sensitivity. When the percentage of training data is 40, the sensitivity of the methods, statistical + BaROA-DCNN, Biomedical+ BaROA-DCNN, and hybrid-BaROA-DCNN is 0.7040, 0.8676, and 0.8945, respectively. Figure 10 c) shows the analysis based on the specificity. When the percentage of training data is 40, the specificity of statistical + BaROA-DCNN, Biomedical+ BaROA-DCNN, and hybrid-BaROA-DCNN is 0.8297, 0.8366, and 0.8856, respectively.



a)



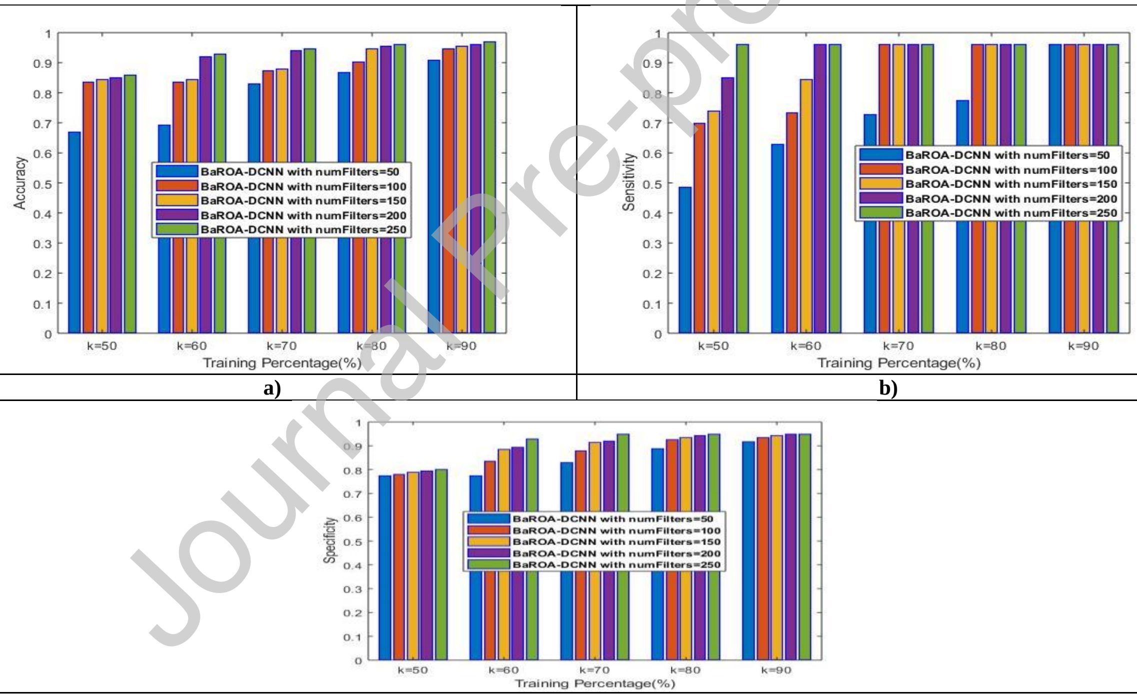
b)



c)

Figure 10. Performance analysis using 100 convolutional layers with iteration count as 500, a) accuracy, b) sensitivity, c) specificity

Figure 11 demonstrates the comparative analysis using ECG signal_1 with respect to the population size. Figure 11 a) shows the analysis based on the accuracy through varying the population size. When the training percentage is 40, the accuracy of BaROA-DCNN with population size 50, 100, 150, 200, and 250 is 0.6702, 0.8366, 0.8434, 0.8503, and 0.8571, respectively. Figure 11 b) shows the analysis based on the sensitivity through varying the population size. When the training percentage is 40, the sensitivity of BaROA-DCNN with population size 50, 100, 150, 200, and 250 is0.4840, 0.6971, 0.7380, 0.8503, and 0.9600, respectively. Figure 11 c) shows the analysis based on the specificity through varying the population size. When the training percentage is 40, the specificity of BaROA-DCNN with population size 50, 100, 150, 200, and 250 is 0.7744, 0.7808, 0.7872, 0.7936, and 0.8000, respectively.



a) b)

c)

Figure 11. Performance analysis using signal_1 based on the number of filters, a) accuracy, b) sensitivity, c) specificity

5. Discussion

This section elaborates the comparative analysis of the proposed method with the existing methods.

5.1 Methods employed for comparative analysis

The methods used for comparison includes: knowledge-based approach [4], Support Vector Machine (SVM) [8], Convolutional Neural Network (CNN) [3], Deep Convolutional Neural Network (DCNN) [44], Genetic Algorithm based Back Propagation Neural Network [47], and convolutional neural network and long short-term memory (CNN+LSTM) [48].

5.2 Comparative analysis

Figure 12 shows the comparative analysis using ECG signal_1. Figure 12 a) shows the analysis of the accuracy of methods through varying the training data percentage. When the percentage of training data is 50, the accuracy of knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, CNN+LSTM, and the proposed

BaROA-DCNN is 48.4%, 83.66%, 84.34%, 84.54%, 84.19%, 84.19%, and 85.03%, respectively. Figure 12 b) shows the analysis based on the sensitivity. When the percentage of training data is 50, the sensitivity of knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, CNN+LSTM and the proposed BaROA-DCNN is 48.4%, 48.8%, 84.34%, 94.52%, 94.51%, 94.16%, and 95%, respectively. Figure 12 c) shows the analysis based on the specificity. When the percentage of training data is 70, the specificity of B knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, CNN+LSTM, and the proposed BaROA-DCNN is 76.06%, 83.65%, 84.34%, 84.27%, 84.19%, 84.19%, and 85.03%, respectively.

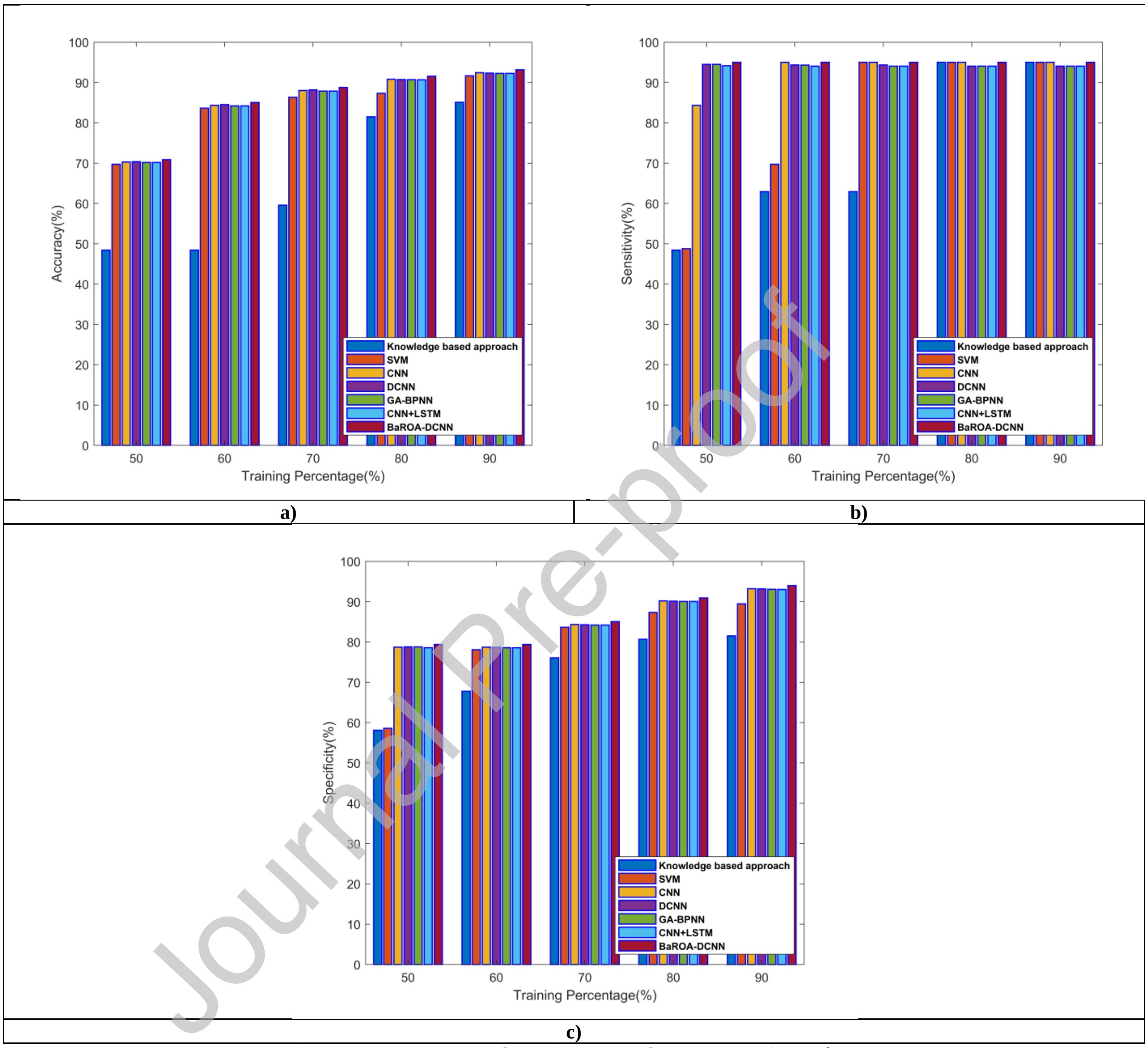
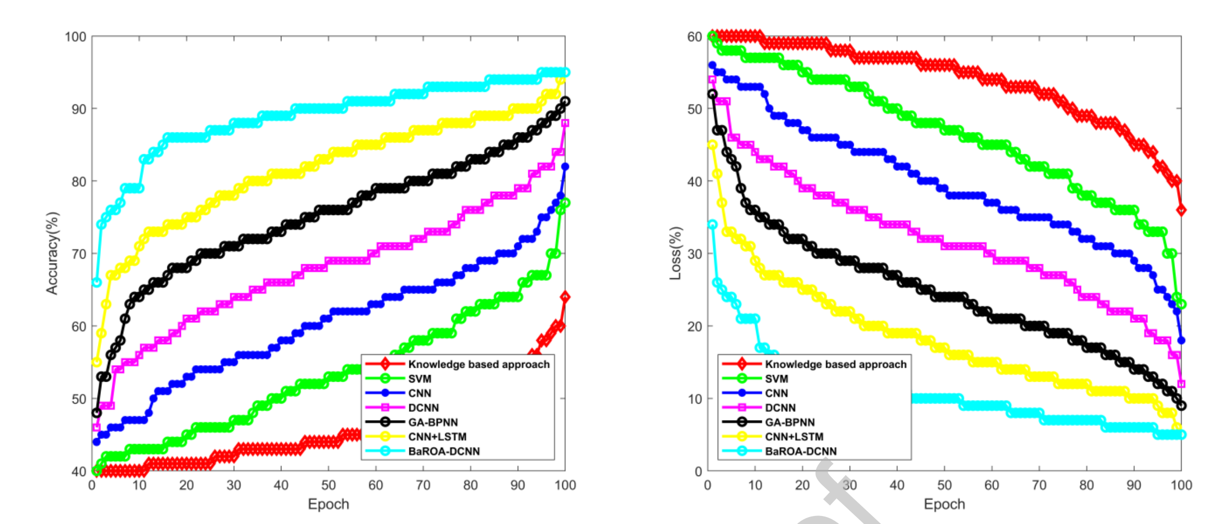


Figure 12. Comparative analysis, a) accuracy, b) sensitivity, c) specificity

5.3 Analysis based on accuracy and loss

This section shows the performance analysis based on accuracy and loss. Figure 13 depicts the performance analysis of the methods, such as knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, CNN+LSTM, and the proposed BaROA-DCNN based on the accuracy and the loss. Figure 13.a. shows the performance analysis based on the accuracy. When the epoch = 50, the accuracy of the methods, such as knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, CNN+LSTM, and the proposed BaROA-DCNN is 44%, 53%, 61%, 69%, 76 %, 83%, and 90%, respectively. For the epoch = 60, the accuracy of the same methods is 46%, 55%, 63%, 70%, 79%, 85%, and 91%, respectively. Figure 13.b. shows the performance analysis based on loss. For epoch = 30, the loss is 88%, 78%, 71%, 64 %, 55%, 47%, and 42%, for the methods, such as knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, CNN+LSTM, and the proposed BaROA- DCNN, respectively. When the epoch = 50, the loss of the methods knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, CNN+LSTM, and the proposed BaROA- DCNN is 90%, 83%, 76%, 69%, 61 %, 53%, and 44%, respectively. The figure clearly shows that the proposed BaROA- DCNN has the maximum accuracy and minimum loss, than the existing methods, such as knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, CNN+LSTM, respectively.



a) b)

Figure 13. Comparative analysis, a) accuracy, b) sensitivity, c) specificity

5.4 Comparative Discussion

The comparative discussion of the methods is deliberated in table 1, in which the best performance is occurred for 90% of training data. The accuracy of the proposed BaROA-DCNN is 93.19, which is 8.71%, 1.62%, 0.8%, 0.91%, 0.99%, and 1%, better than the existing methods, such as knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, and CNN+LSTM, respectively. The maximum sensitivity of the methods, such as knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, CNN+LSTM, and the proposed BaROA-DCNN is 95%, 95%, 95%, 94.05%, 94.05%, 94.05%, and 95%. The performance difference of the proposed BaROA-DCNN, over the existing methods, such as knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, and CNN+LSTM is 13.26%, 4.8%, 0.81%, 0.87%, 0.96%, and 0.99%. Thus, the accuracy, sensitivity, and specificity of the proposed BaROA-DCNN is better than the existing methods, such as knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, and CNN+LSTM.

Table 1. Comparative discussion

Methods	Accuracy (%)	Sensitivity (%)	Specificity (%)
knowledge-based approach	85.07	95	81.52
SVM	91.68	95	89.47
CNN	92.44	95	93.22
DCNN	92.34	94.05	93.16
GA-BPNN	92.27	94.05	93.08
CNN+LSTM	92.26	94.05	93.05
proposed BaROA-DCNN	**93.19**	**95**	**93.98**

Table 2 shows the computational complexity of the proposed BaROA-DCNN, and the existing methods, such as knowledge-based approach, SVM, CNN, DCNN, GA-BPNN, and CNN+LSTM, in which the proposed system has the minimum computation time of 6.12 sec.

Table 2. Computational Complexity

Methods	knowledge-based approach	SVM	CNN	DCNN	GA-BPNN	CNN+LSTM	proposed BaROA-DCNN
Time (Sec)	13.07	11	10.4	9.02	8	7.25	**6.12**

6. Conclusion

In this paper, the automatic method of arrhythmia classification is performed using the proposed Bat-Rider Optimization algorithm-based deep convolutional neural networks (BaROA-based DCNN). Initially, the ECG signals are fed to the feature extraction module using which the features corresponding to the waves, such as the PR interval, PP interval, R peak, QT interval, and RR interval are extracted and in addition, the gabor features are obtained. The features are fed to the arrhythmia classification module, which classifies the patient as either affected with arrhythmia or normal. The classifier Deep CNN yields an accurate classification and it is an automatic way of classification. The classification accuracy is the benefit of the proposed BaROA in training the classifier. The experimentation is performed using the MIT-BIH Arrhythmia Database and the analysis is performed based on the evaluation metrics. The proposed method of arrhythmia classification acquired the maximal values of 93.19%, 95%, and 93.98%, for accuracy, sensitivity, and specificity, respectively. The multi-objective handling ability is the major advantage of the proposed system. Anyhow, this method needs to be improved in dynamic features handling. The future extension of the research is based on any other optimization algorithms and classifiers, which rendered much better performance. Also, the dynamic features handling, experimentation using raw input signal, and the experimentation with more datasets will be considered in our future work.

Conflicts of Interest Declaration

This is to certify that all Authors have seen and approved the manuscript being submitted and we have no conflict of interest to declare.

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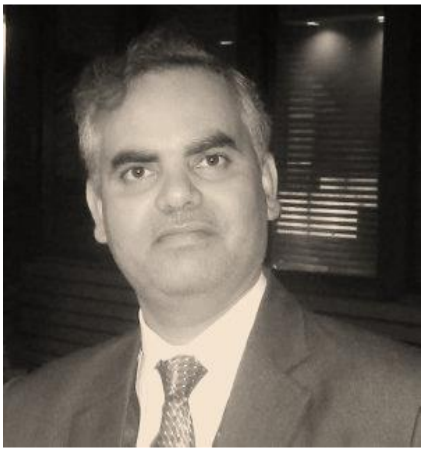

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