IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 14 August 2023, accepted 26 August 2023, date of publication 6 September 2023, date of current version 19 September 2023.

*Digital Object Identifier 10.1109/ACCESS.2023.3312537*

RESEARCH ARTICLE

# Feature Selection Using Selective Opposition Based Artificial Rabbits Optimization for Arrhythmia Classification on Internet of Medical Things Environment

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This work was supported in part by the Rector of the Silesian University of Technology under Proquality under Grant 09/010/RGJ23/0076, and in part by the Spanish Research Projects under Grant P18-RT-1994 and Grant PID2020-119082RB-C21.

**ABSTRACT** An Electrocardiogram (ECG) is a non-invasive test that is broadly utilized for monitoring and diagnosing the cardiac arrhythmia. An irregularity of the heartbeat is generally defined as arrhythmia, which potentially causes the fatal difficulties that creates an instantaneous life risk. Therefore, the arrhythmia classification is a challenging task because of the overfitting issue caused by high dimensional feature space of ECG signal. In this research, the incorporation of the Internet of Medical Things (IoMT) is developed with artificial intelligence to provide the health monitoring for people who are having arrhythmia. In this work, the time, time-frequency, entropy, nonlinearity features of ECG and deep features of ECG from Convolutional Neural Network (CNN) are extracted to obtain different categories of ECG signal features. The Selective Opposition (SO) strategy based Artificial Rabbits Optimization (SOARO) is proposed for selecting the optimal feature subset from the overall features to avoid the overfitting issue. The chosen features are used to improve the classification done by Auto Encoder (AE). Further, the Shapley additive explanations (SHAP) based model is used to interpret the classified output from AE. The MIT-BIH arrhythmia database is used for evaluating the proposed SOARO-AE. The performance of the proposed SOARO-AE is evaluated by using the accuracy, sensitivity, specificity, recall and F1-Measure. The existing researches such as C-LSTM, DL-LAC-CNN, CNN-DNN, MC-ECG, FC and MEAHA-CNN are used to evaluate the SOARO-AE method. The accuracy of SOARO-AE is 98.89% which is high when compared to the C-LSTM, DL-LAC-CNN, CNN-DNN, FC and MEAHA-CNN.

**INDEX TERMS** Arrhythmia, artificial rabbits optimization, auto encoder, electrocardiogram, health monitoring, internet of medical things, selective oppositio.

The associate editor coordinating the review of this manuscript and approving it for publication was Huaqing Li.

## I. INTRODUCTION

The Internet of Things (IoT) standard defined in Internet of Medical Things (IoMT) provides the reliable communication of huge range of data streams which is evaluated to obtain the vital data about the condition of patient. The tremendous application of IoMT is linked with the treatment of cardiovascular diseases (CVD) that ensured the continuous collection of a widespread range of data for extracting the information from patient [1]. The Remote ECG observation system, monitoring center server, network communication support and ECG monitoring mobile phone terminal are extensively utilized in medical treatment. The health condition of patient is observed and classified in real time using the collected ECG signal in the telemetry systems [2]. The heart disease or CVD are the circumstances in which the functions or structure of heart is affected in worldwide. The CVD is an important cause of early mortality and the key reason of disease among all non-communicable. Additionally, the predominant types of heart diseases affect the humans are Arrhythmia, Myocardial Infarction, Dilated Cardiomyopathy, Coronary Artery Disease, Mitral Valve Prolapse, Aortic Stenosis, Mitral Valve Regurgitation and Congenital Heart Defects [3], [4].

Arrhythmia denotes the irregular heart rhythm where the heart beat is either too slow or too fast that is considered as one of the main reasons of CVD death [5], [6]. A regular observation and analysis of ECG signals are used to prevent, diagnose and control the different CVDs. Therefore, the observation of physical signals like ECG signals offers the computation of CVD and supports the prevention and control of disease [7]. ECG evaluates the tiny electrical impulses generated by heart which is generally utilized for identifying the different heart diseases [8], [9], [10]. In heart disease analysis, the problem is occurred in some places where there are is the absence of clinical equipments and specialists, especially in growing and developing countries. Therefore, the computer-aided diagnosis technologies are developed to ensure the automatic monitoring and deliver the straightforward solutions for keep the individuals know about their diseases [11], [12]. The incorporation of IoMT with artificial intelligence provides the incredible assistances in health care. IoMT is developed for transferring the details about the patients for monitoring purpose and AI is used to assist the IoMT in terms of diagnosis [13]. During the diagnosis, the reliability is minimized because of the artifacts and interferences exists in ECG signal [14], [15]. Moreover, the processing of high dimensional features space in artificial intelligence causes the overfitting [16].

As motivated by different health prediction systems growth for decreasing the mortality rate and to overcome aforementioned issues, the proposed system is developed the Arrhythmia classification with Internet of Medical Things (IoMT). The research contributions are concise as follows:

- Features of various domains such as time, time-frequency, entropy, nonlinearity and deep features from CNN are extracted for acquiring different categories of features. In that, the variation of signal over time is expressed by time domain, distribution of signal energy through frequency range is denoted by frequency domain, chaotic behaviour in vibration signals is characterized by nonlinear features and uncertainty of the information is computed by entropy. Therefore, the hand crafted features such as time, time-frequency, entropy and nonlinearity are combined with deep features of CNN provides the appropriate information about ECG signal.
- The high dimensional feature space causes the overfitting during the classification. The SOARO based feature selection is developed to choose the relevant features according to accuracy and F1 score which helps to avoid the overfitting issue. The SOARO considered the multiple fitness measures for discovering the optimal feature set according to the best trade-off between accuracy and F1 score. Here, the SOARO is chosen because of its varying proximity dimension of rabbits that used to obtain the better searching of optimal feature subset from overall features.
- The IoMT framework is used for performing the health monitoring of people's who are having arrhythmia.

The remaining paper is sorted as follows: Section II provides the related work information about the Arrhythmia classification with IoT. The problem statement along with the solutions given by the SOARO-AE is given in section III. The detailed explanation about the SOARO-AE with IoHT is provided in section IV whereas the results are provided in section V. Further, the discussion and conclusion are given in section VI and VII respectively.

## II. RELATED WORK

The related works information about the Arrhythmia classification with IoT are provided in section II.

### A. ARRHYTHMIA CLASSIFICATION WITH IoT

Lu et al. [17] presented Convolutional Neural Network (CNN) - Long short-term memory network (LSTM) namely C-LSTM based network model to classify the arrhythmia. At first, the ECG signals were encoded and morphological features were extracted by using a deep CNN. The intrinsic features were deeply extracted using the temporal correlation of LSTM morphological feature representation. Next, the arrhythmia classification was done according to the features of ECG signal. The IoHT was used in this research for monitoring the health data. A learning of ECG data using C-LSTM was used to improve the monitoring and analysis. The indirect features of arrhythmia were missed, when the classifier was processed with only data segment of heart beat which affected the classification.

Sakib et al. [18] developed the arrhythmia classification using ECG signals to perform smart ultra-edge health monitoring for the desired users. The Deep Learning-based Lightweight Arrhythmia Classification (DL-LAC) with CNN was developed and it used the raw single-lead ECG for arrhythmia classification. The developed DL-LAC was not required noise-filtering that made the system light weight and integration was easy with ultra-edge node. The utilization of entire feature set was led to cause the overfitting issue during the classification.

Yeh et al. [19] presented the CNN for classifying the ECG for supporting the anesthesia assessment. The IoT was utilized for developing the computation prototypes of ECG signal. Meanwhile, the Deep Neural Network (DNN) was used to categorize the signal type. The developed IoT based monitoring was used doctors to act according to health status. The developed approach directly performs the classification without any feature extraction. The statistical features e.g., time and frequency domain features were minimum requirement for analysing the signal distribution over time and signal energy distribution through frequency range.

Dami and Yahaghizadeh [20] developed the LSTM for predicting and analysing the heart diseases. Further, the Deep Belief Network (DBN) based feature representation was developed for minimizing the data size and choose appropriate features. Therefore, this LSTM-DBN was used to predict the heart disease or event and broadcasted the location of patient for all stakeholders. The developed DBN was suitable for large number of samples which were stored in batches for construing that used to obtain faster learning. However, the small number of samples was not sufficient to build multilevel layer-by-layer structure.

Devi and Kalaivani [21] presented IoT based ECG monitoring for evaluating the ECG signal. From the ECG signal, the statistical features were acquired while Pan Tompkins QRS detection was used to acquire the dynamic features. The features of heart rate inconsistency were used to discover the RR intervals. The combination of dynamic and statistical features was used to improve the classification using Support Vector Machine (SVM). However, the classifier used in this work was not suitable for multi class classification. For an effective evaluation of ECG signal, multi class classification was required to be performed to analyse the different type of diseases.

Prajitha et al. [22] developed the Variance Approximation and Probabilistic Decomposition Noise Removal method (VA-PDNR) for denoising the ECG signal to do detection and categorization of arrhythmia. The operational variables were controlled by using VA for minimizing the high-frequency noise which used to reduce the variance in noise. The power line interference was divided into various mode parameters using PDNR and eliminating the noise by Linear Quadratic Estimation. The redundancies were removed by using the dimension-reduction and examined the characteristic textural features. Further, these hybrid features were given to artificial neural network to classify the Arrhythmia. However, the classification performance of VA-PDNR was varied with the changes in frame size.

He et al. [23] presented the IoT with ECGs to develop the framework of arrhythmia detection. The developed framework has two different modules such as data cleaning and heartbeat classification. The Dynamic Heartbeat Classification with Adjusted Features (DHCAF) and Multi-channel Heartbeat CNN (MCHCNN) were developed for classifying the heartbeat. The multi-channel convolutions were accomplished in MCHCNN for acquiring the temporal and frequency patterns. The dynamic ensemble selection and result regulator were used in DHCAF for enhancing the classification. The classification of S beat was not improved than the other beats which led to affect the overall classification.

### *B. FEATURE SELECTION BASED ARRHYTHMIA CLASSIFICATION*

Nasim and Kim [24] developed the Differential Evolution (DE) for optimizing the amplitude features of direct ECG heartbeat. This DE based feature optimization was increased the Matthews correlation coefficient (MCC) for 8 arrhythmia beat classes has uncorrelated and imbalanced class distributions. The developed DE was tuned to discover the less optimum feature combination that used to eliminate noisy or unwanted signal points. Further, the classification was done by using probabilistic neural network with chosen features. The developed DE approach was not considered the accuracy during the feature subset selection. The incorporation of accuracy was used to identify features with higher probability of precise classification.

Houssein et al. [25] presented the various ECG signal descriptors according to the higher-order statistical, wavelet, morphological and one-dimensional local binary pattern for extracting the features. An automatic determination of significant features was obtained by combining the Manta ray foraging optimization (MRFO) with SVM. In MRFO-SVM, the SVM parameters were optimized by MRFO as well as this MRFO used to choose the significant features for improving the classification. The SVM used in this research was processed for limited number of classes. A multi class classification was required to be developed for an effective diagnosis,

Li et al. [26] developed the multi-label feature selection approach according to ECG and kernelized fuzzy rough sets was used to select the feature subset. Next, the multi-label classification of arrhythmia according to ECG (MC-ECG) was developed by Multi Objective Optimization (MOO). This MOO depends on the sparsity constraint, mapping relationship among ECG features & arrhythmia diseases which used to achieve enhanced classification. Piri and Mohapatra [27] presented the Multi-Objective Quadratic Binary Harris Hawk Optimization (MOQBHHO) with K-Nearest Neighbor (KNN) for extracting the adequate feature subsets. The crowding distance was utilized as third criterion in MOQBHHO to select the optimum solution from non-dominated solutions. An inappropriate selection of fitness measures creates a huge impact during the classification.

Chen et al. [28] developed the combination of CNN and LSTM for an automatic identification of ECG signal. The CNN and LSTM were used in the signal abstraction procedure whereas the spatial feature was obtained using CNN and time feature was obtained using LSTM. The combination of spatial and time feature were used to enhance the classification process. However, the handcrafted features was obtained domain-specific information and prior knowledge that does not efficiently obtained only by using the CNN.

Essa and Xie [29] presented the deep learning-based multi-model approach for ECG signal classification. Two deep learning bagging models such as CNN-LSTM and RR intervals and Higher-Order Statistics (RRHOS)-LSTM network were developed for acquiring the local features and temporal dynamics of ECG. These two models were used to generate the bagging model for handling the issue of higher imbalance. Further, the CNN-LSTM and RRHOS-LSTM were integrated as on Fusion Classifier (FC). Rahul and Sharma [30] developed the hybrid 1-D CNN and Bi-LSTM to accomplish an classification of cardiac arrhythmia. At first, the ECG signal was preprocessed using stationary wavelet transforms and a two-stage median filter with savitzky–golay filter. Next, the segmentation and z-score normalization were carried out for an ease of mapping during the classification. The 1-D CNN and Bi-LSTM were used to extract the features and classify the ECG signal. This classifier was required to eliminate some of the classes from ECG signal for better performances.

Kıymaç and Kaya [31] presented the hyperparameter optimization using metaheuristic approach for improving the classification using CNN. The Memory-Enhanced Artificial Hummingbird Algorithm (MEAHA) was used to optimize the hyper parameters of CNN. The selection of optimal parameters was mandatory for further enhancing the CNN classification.

The research gap from the related works are inadequate feature extraction, avoiding the issue of overfitting and processing of classifiers with all the extracted features. Therefore, the required features such as the time, time-frequency, entropy, nonlinearity and deep features are extracted to improve the representation and discrimination of ECG signal. Further, a unwanted features from the overall features are eliminated by using SOARO which leads to overcome the issue of overfitting during the classification.

## III. PROBLEM IDENTIFICATION

The problems found from the related works are given in this section along with the solution given by the proposed SOARO-AE method.

The classification of arrhythmia is affected when the classifier is processed under the following conditions: missing of indirect features [17] and overfitting issue [18], [20]. Different categories of features are required to be extracted for improving the classification [19]. The solutions given by the SOARO-AE method are given as follows: The different categories of features such as time, time-frequency, entropy, nonlinearity and deep features from CNN. The reason for considering different categories of features are given as follows: A different in signal with time is expressed by time domain, signal energy distribution through frequency range is denoted by frequency domain, chaotic behaviour in vibration signals is denoted by nonlinear features, uncertainty of the data is computed by entropy and deep features are extracted by using CNN. In that, the variation of signal over time is expressed by time domain, distribution of signal energy through frequency range is denoted by frequency domain, chaotic behaviour in vibration signals is characterized by nonlinear features and uncertainty of the information is computed by entropy. Further, the irrelevant features from the overall feature set is chosen by using the SOARO which is optimized by accuracy and number of features. Further, the AE classification is done and the IoMT framework is used for monitoring the patients who are having arrhythmia.

## IV. SOARO-AE METHOD

In this research, an effective feature selection is performed by using the SOARO where the selection of feature subset is optimized by considering the accuracy and number of features. Initially, the EMD is used for decomposing the ECG signal into Intrinsic Mode Functions (IMF). The different categories of ECG features are extracted and SOARO based feature selection is done to remove the irrelevant features which used to avoid the overfitting issue. Further, classification is done by using AE classifier followed by SHAP model is used to interpret the outputs from AE. The IoMT framework is used for performing the health monitoring of people's who are having arrhythmia. In IoMT framework, the details about the patients who are collected and transmitted from device to other medium i.e., between the Doctors. The developed IoMT framework is used in remote locations. Moreover, the entire medical history is stored for medical purposes. The block diagram of the SOARO-AE with IoMT is shown in the Fig. 1.

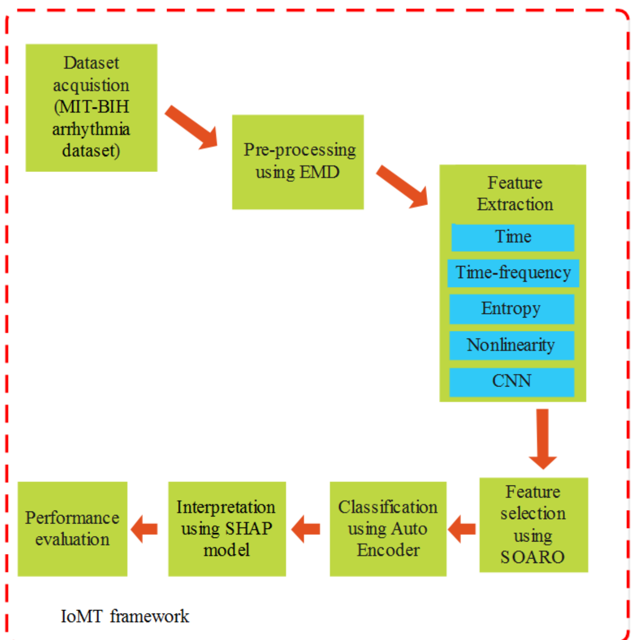


**FIGURE 1. Block diagram of the SOARO-AE with IoMT.**

### A. DATA ACQUISITION

The proposed method is validated and simulated using the ECG signals from MIT-BIH arrhythmia [32] dataset. The raw ECG signal is obtained has 48 ECG records which is acquired from 47 subjects aged among 23 to 89 years.

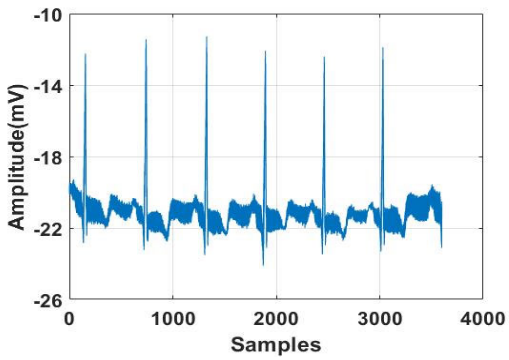


**FIGURE 2.** Sample ECG signal from first electrode of MIT-BIH arrhythmia dataset.

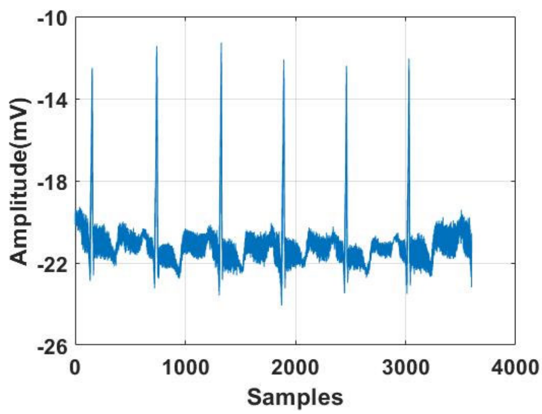


**FIGURE 3.** Noisy ECG signal.

Here, the data from the first electrode is considered for evaluation. The records are digitized with 360 Hz sampling frequency with the resolution of 11-bit/sample. According to the Association for the Advancement of Medical Instrumentation (AAMI) standard, the beats in the MIT-BIH dataset is combined into five classes such as Normal Beat (NB), Supraventricular Ectopic Beat (SEB), Ventricular Ectopic Beat (VEB), Fusion Beat (FB) and Unknown Beat (UB). In MIT-BIH arrhythmia dataset, two different electrodes are used to collect the ECG signals. In that dataset, the patient ID 100 has around $2 \times 650000$ samples. The first 10 s ECG signal of the patient ID 100 collected from first electrode is shown in the Fig. 2. The noisy signal generated for analysing the real time evaluation is shown in Fig. 3. Here. 10 dB white noise is added to ensure the classification for satisfying the real time requirements.

### B. PRE-PROCESSING USING EMD

EMD [33] is used as the pre-processing for denoising which is a time-frequency domain signal analysis which adaptively decomposes non-stationary time series signal into sum of oscillatory waveforms referred as Intrinsic Mode Functions (IMF). The IMF denotes the frequency modulated components and zero-mean amplitude. The major principle of this ECD is to detects the intrinsic oscillatory modes according to the characteristic time scales of data and the EMD decomposes the data.

The EMD based pre-processing are mentioned as follows:

1. The cubic spline is applied for correlating the local minimum and maximum for creating the lower and upper envelope.
2. Denote the average lower and upper envelopes that is mentioned as $m_1(t)$.
3. Compute the difference among the signal $y(t)$ and average $m_1(t)$, $i_1(t) = y(t) - m_1(t)$ i.e., potential first IMF.
4. The two necessities of IMF are required to be satisfied by $i_1(t)$.
   - In the overall data, an amount of zero crossings and extreme is required to be differ or equal or differ by no more than one.
   - The local maximum denotes the envelope's mean value and local minimum is 0 at any point.

   The $i_1(t)$ is the 1st IMF of the signal $y(t)$, when $i_1(t)$ satisfies both the aforementioned requirements. Otherwise, the reiterating process of sifting over $i_1(t)$ is done until it satisfies the requirements.
5. The data is divided as $n$ IMFs by reiterating using sifting process, once the $y(t)$ is subtracted from IMF.

Equation (1) expresses the signal $y(t)$.

$$y(t) = \sum_{j=1}^{n} IMF_j(t) + r_n(t) \tag{1}$$

where, the input signal is denoted as $y(t)$; $IMF_j(t)$ specifies the IMFs ($j = 1, 2, 3, \ldots, n$) i.e., $n = 12$, and residue is denoted as $r_n(t)$. The IMF signal from EMD and denoised ECG signal is shown in Figs. 4 and 5 respectively.

### C. FEATURE EXTRACTION

In this phase, a pre-processed ECG signal is processed under different feature extraction methods such as time, time-frequency, entropy, nonlinearity and CNN based feature extraction. Each ECG signal is divided as multiple 10s of signal whereas each divided signal does not have an individual label. In order to overcome this issue, the CNN is required to discriminate the ECG signal features. Because, the statistical features such as time, time-frequency, entropy, nonlinearity are not provided the enough information to classify the ECG signal. Therefore, the statistical features are combined with the deep features from CNN for enhancing the classification.

The detailed information about feature extraction is given as follows:

#### 1) TIME AND TIME-FREQUENCY BASED FEATURES

The time domain features considered in this proposed method are standard deviation (SD), Hjorth parameters and Mean Absolute Value (MAV) whereas the Discrete Wavelet

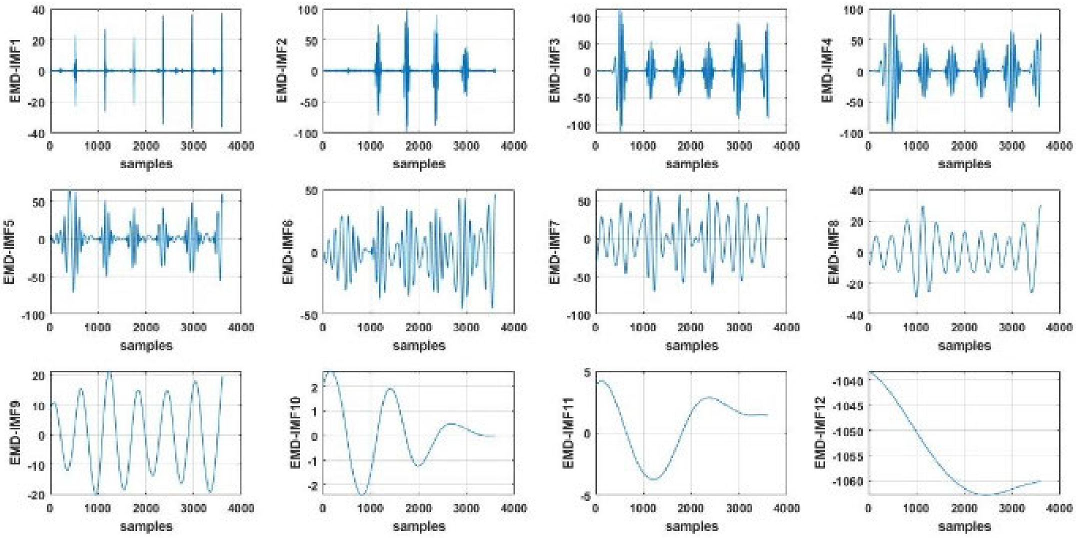


**FIGURE 4.** IMF signal from EMD.

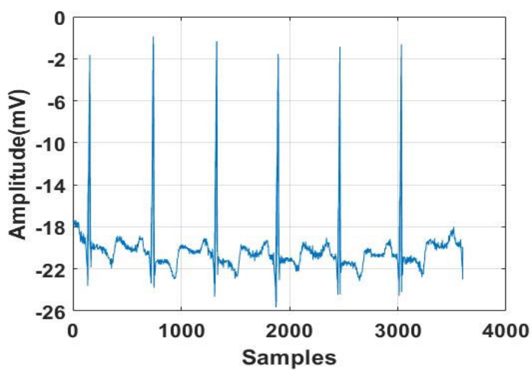


**FIGURE 5.** Denoised ECG signal using EMD.

Transform (DWT) is taken for time-frequency based feature. The details for time and time-frequency features are given as follows:

- SD [34] is one the statistical parameter which used to denote the amplitude and dissemination of time series. Here, the SD is computed for analysing the amount of dispersion in the RR interval with its mean. The difference among the ECG's each sample and their mean value is defined as SD which is expressed in (2).

$$SD = \sqrt{\left[\frac{1}{N-1}\sum\nolimits_{i=1}^{N}(y_i - \bar{y})^2\right]} \tag{2}$$

  where, $y_i$ is pre-processed ECG signal; number of samples is denoted as $N$ i.e., 3600 samples; mean value of ECG signal is denoted as $\bar{y}$.

- MAV [34] expressed in (3) is computed based on the average of absolute value of the ECG signal for 10 s interval.

$$MAV = \frac{1}{N}\sum\nolimits_{i=1}^{N}|y_i| \tag{3}$$

- The Hjorth parameter [35] is a feature comprises of activity, mobility, and complexity which is acquired in time domain. The signal amplitude difference is activity which defines the average power. Mobility is the square root of signal magnitude's variance in signal slope's variance and denotes the mean frequency. The closeness of signal resembles a pure sine wave is denoted as complexity. The Hjorth parameters of activity, mobility, and complexity are denoted in (4), (5) and (6) respectively. Here, the calculation of signal difference is activity; mean frequency of signal is denoted as mobility and signal deviation from sine shape is denoted as complexity.

$$Activity = \sigma_1 \tag{4}$$

$$Mobility = \sqrt{\frac{\sigma_2}{\sigma_1}} \tag{5}$$

$$Complexity = \sqrt{\frac{\sigma_3/\sigma_2}{\sigma_2/\sigma_1}} \tag{6}$$

where, the variance of $y(t)$ is denoted as $\sigma_1$, derivative and 2nd order derivative of variance are denoted as $\sigma_2$ and $\sigma_3$ respectively. Equations (7), (8) and (9) expresses the $\sigma_1$, $\sigma_2$ and $\sigma_3$ respectively.

$$\sigma_1 = \frac{1}{N}\sum\nolimits_{i=1}^{N} y_i^2 \tag{7}$$

$$\sigma_2 = \frac{1}{N-1}\sum\nolimits_{i=1}^{N-1}(y_{i+1} - y_i)^2 \tag{8}$$

$$\sigma_3 = \frac{1}{N-2}\sum\nolimits_{i=1}^{N-2}((y_{i+2} - y_{i+1}) - (y_{i+1} - y_i))^2 \tag{9}$$

- The wavelet transform is referred as DWT [36], when the wavelets are individually sampled in the feature extraction process. The wavelet coefficient features of denoised DWT are used as time-frequency features.

The concatenated features of time and time-frequency domain is expressed in (10).

$$CF = \{SD, MAV, Activity, Mobility, Complexity, DWT \tag{10}$$

The variation of signal over time is expressed by time domain as well as the signal energy distribution through frequency range is denoted by frequency domain features.

### 2) ENTROPY BASED FEATURES

The calculation of Log Energy Entropy (LEE) [37] expressed in (11) is accomplished to estimate the complexity degree of pre-processed ECG signals.

$$LEE = \sum\nolimits_{i=1}^{N} \log y_i^2 \tag{11}$$

Entropy is used to compute the uncertainty information of ECG signal.

### 3) NONLINEAR-BASED FEATURES

The Mean Teager Energy (MTE) and Mean curve length (MCL) [38] are taken to extract non-linear features. MTE expressed in (12) is used for an effective energy tracking of signals. MCL of (13) is offered the evaluation of Katz fractal dimension that utilized for identifying the activities of ECG.

$$MTE = \frac{1}{N}\sum\nolimits_{t=3}^{N}\left(y\left(t-1\right)^2 - y(t)y(t-2)\right) \tag{12}$$

$$MCL = \frac{1}{N}\sum\nolimits_{t=2}^{N}\left(y\left(t\right) - y(t-1)\right) \tag{13}$$

The chaotic behaviour in vibration signals is characterized by nonlinear features.

### 4) CNN BASED FEATURE EXTRACTION

The acquired each ECG signal is divided with a particular time frame i.e., 10s. So, the divided multiple signals from an each ECG signal are either from normal class or from abnormal classes i.e., remaining four classes such as supraventricular ectopic beat, ventricular ectopic beat, fusion beat and unknown beat. However, the each ECG signal has only one label, it doesn't contain the individual label for each time frame. In order to overcome the aforementioned issue, the CNN feature are used for a better representation of each time frame. The CNN model namely ResNet-50 [39] is used for the extraction of deep features from the pre-processed ECG signals. The residual block incorporated in the ResNet-50 is used to minimize the impact of gradient explosion and disappearance generated by maximizing the network depth. The ResNet-50 preserves huge amount of data to learn in training process by overlapping the original nonlinear features with the nonlinear features obtained from the residual blocks. The ResNet-50 architecture has depth of 50 layers during the feature extraction. This ResNet-50 has fully connected layer and these layers are utilized for extracting the deep features. Specifically, the features are extracted from 49th fully connected layer of ResNet-50. The concatenated features from time, time-frequency, entropy, nonlinearity and CNN is expressed in (14).

$$z = \{CF, LEE, MTE, MCL, CNNfeatures \tag{14}$$

The extracted features with a length of 2068 are given as input to the SOARO based feature selection.

## D. FEATURE SELECTION USING SOARO

The SOARO receives the input from the feature extraction where the extracted features has different categories of pre-processed ECG signal. The conventional ARO [40] is motivated by the survival strategies of rabbit in the wild. The ARO uses the strategies of searching and hiding while the energy minimization is done for making the conversion among the strategies which helps to solve the optimization problem. The iterative process of SOARO has different phases such as exploration, conversion from exploration to exploitation, and exploitation. Further, this SOARO is processed with maximum iteration 100 and population size of 40.

### 1) EXPLORATION (DETOUR FORAGING)

Each rabbit in the SOARO is considered its individual area with few grass and burrows. The rabbit randomly moves away from their individual area during the searching to forage the food and monitor what exists in adjacent area. The exploration is denoted as detour foraging and it is depicted in (15) to (20).

$$\begin{aligned} z_i\left(t+1\right) &= z_j\left(t\right) + A \times \left(z_i\left(t\right) - z_j\left(t\right)\right) \\ &\quad + round\left(0.5 \times \left(0.05 \times R_1\right)\right) \times q_1, \end{aligned} \tag{15}$$

$$A = L \times c \tag{16}$$

$$L = \left(e - e^{\left(\frac{t-1}{T}\right)^2}\right) \times \sin\left(2\pi R_2\right) \tag{17}$$

$$c\left(k\right) = \begin{cases} 1, & if\ k == g(l) \\ 0, & otherwise, \end{cases} \quad k = 1, \ldots, D\ and$$

$$l = 1, \ldots, \lceil R_3 \times D \rceil \tag{18}$$

$$g = randperm(D) \tag{19}$$

$$q_1 \sim P(0,1) \tag{20}$$

where, $i, j = 1, \ldots, P$ and $i \neq j$; candidate position of $i$th rabbit at iteration $t+1$ is denoted as $z_i\left(t+1\right)$; $z_i\left(t\right)$ and $z_j\left(t\right)$ denotes $i$th and $j$th rabbit location for iteration $t$; $P$ denotes population size; $t$ and $T$ specifies the current and maximum iteration; $D$ denotes the dimension; $\lceil . \rceil$ denotes the ceiling function; $round(.d)$ specifies the rounding close to the integer; $randperm$ is the integer selected randomly between $[1,D]$; $R_1$, $R_2$ & $R_3$ specifies the random value among [0, 1]; $q1$ denotes the standard normal distribution and $L$ is movement step length.

### 2) CONVERSION FROM EXPLORATION TO EXPLOITATION

The detour foraging is accomplished by rabbits in the initial phase of iteration whereas the random hiding is frequently executed in the following stages of foraging process. Equation (21) expresses the rabbit energy $RE$ that is incorporated to maintain the trade-off between exploitation and exploration.

$$E(t) = 4\left(1 - \frac{t}{T}\right)\ln\frac{1}{R_4} \tag{21}$$

where, $R_4$ specifies the random value in the range of [0, 1]. The value $E$ is changed among the range of [0, 2]. The rabbit has higher energy, when $E > 1$ to randomly explore the area of other rabbits, hence detour foraging is done that is referred as exploration. On the other hand, the random hiding is performed by rabbit, when $E \leq 1$ that used to eliminate the predation (exploitation phase).

### 3) EXPLOITATION (RANDOM HIDING)

The predator chases/ attacks the rabbits in exploitation phase. Accordingly, the rabbits create different holes close to the nest for shelter. A rabbit made $D$ holes along with the search space dimension and randomly selects any one hole for decreasing the capture probability. Equations (22) to (26) depicts the process of random hiding.

$$z_i(t+1) = z_i(t) + A \times \left(R_5 \times b_{i,r}(t) - z_i(t)\right) \tag{22}$$

$$b_{i,r}(t) = z_i(t) + H \times g_r(k) \times z_i(t) \tag{23}$$

$$g_r(k) = \begin{cases} 1, & if\ k == \lceil R_6 \times D \rceil \\ 0, & otherwise \end{cases} \tag{24}$$

$$H = \frac{T - t + 1}{T} \times q_2 \tag{25}$$

$$q_2 \sim P(0, 1) \tag{26}$$

where, $b_{i,r}(t)$ denotes the randomly selected hole of $i$th rabbit from holes $D$ used for hiding in $t$th iteration; $R_5$ & $R_6$ specifies the random value between [0, 1], and $q_2$ is standard normal distribution.

### 4) SELECTIVE OPPOSITION STRATEGY

The strategy of SO [41] is modified principle of opposition-based learning which modified the rabbit size far from best solution. Subsequently, the modified rabbit population are making it close to the rabbit in the optimal location. The strategy of SO is affected because of linearly decreasing threshold. The SO supports the assists for obtaining the optimal solution during the development phase by altering the proximity dimension of various rabbits.

The steps processed in SO are mentioned as follows:

- At first, the threshold ($TS$) is required to be defined as shown in (27). According to (28), the SO verifies each candidate rabbit's distance between the current rabbit dimension and best rabbit for all rabbits in the population.

$$TS = 2 - \left(t \times \frac{2}{T_{max}}\right) \tag{27}$$

$$dd_j = \left|z_{ibest,j} - z_{i,j}\right| \tag{28}$$

where, $T_{max}$ is maximum iteration; distance for all dimensions of each rabbit is denoted as $dd_i$; A nearby and far rabbit locations are computed, when the $dd_j$ is higher than $TS$. Subsequently, all the different distances of all rabbit locations are listed in this SOARO.

The $src$ of (29) is used to compute the correlation among the current and optimal rabbit. Consider, that $src < 0$ and far dimension ($D_f$) is higher than close dimensions ($D_c$), the location of rabbit updated based on (30).

$$src = 1 - \frac{6.\sum_{j=1}\left(dd_j\right)^2}{dd_j \times (dd_j^2 - 1)} \tag{29}$$

$$z'_{Df} = lb_{Df} + ub_{Df} - z_{Df} \tag{30}$$

Based on the aforementioned (30), the rabbit position is updated and optimal feature subset is selected from the overall feature set.

### 5) FITNESS FUNCTION OF SOARO

The SOARO chooses the optimal features based on two different finesses such as classification accuracy and the F1-measure that is denoted in (31).

$$Fitness(\vec{z}_i) = \vartheta \times Acc(\vec{z}_i) + \delta \times F1 - measure(\vec{z}_i) \tag{31}$$

where, the random feature subset is denoted as $\vec{z}_i$; accuracy of $\vec{z}_i$ is denoted as $Acc(\vec{z}_i)$; F1-measure of $\vec{z}_i$ is denoted as $F1 - measure(\vec{z}_i)$; $\vartheta$ and $\delta$ are the random value among the range of [0, 1]. These random numbers are used to depict the connection among the accuracy and F1-measure. For each iteration, the fitness of $\vec{z}_i$ is evaluated and $\vec{z}_i$ with best fitness ($\vec{z}_{ibest}$) is chosen as optimal feature subset.

The Pseudo code for optimum feature selection using SOARO is given in following Algorithm 1 and flowchart for SOARO is shown in Fig. 6.

The developed SOARO is executed, until it reaches the maximum iterations. The SOARO selects feature subset with a length of 1053 which is given as input to AE for classifying the arrhythmia.

## *E. CLASSIFICATION USING AUTO ENCODER AND INTERPRETATION USING SHAP*

The extracted features using SOARO is given as input to the AE [42] which is shown in the Fig 7. This AE processes extra features as model input over the hidden layers and reconstructed the output. The AE acquires the features in the internal structure and transmits them to output layer in reconstruction phase. The encoder and decoder operations are executed by AE. The operation of encoder is performed among the input and hidden layer. Next, the operation of decoder is performed among the hidden and output layer.

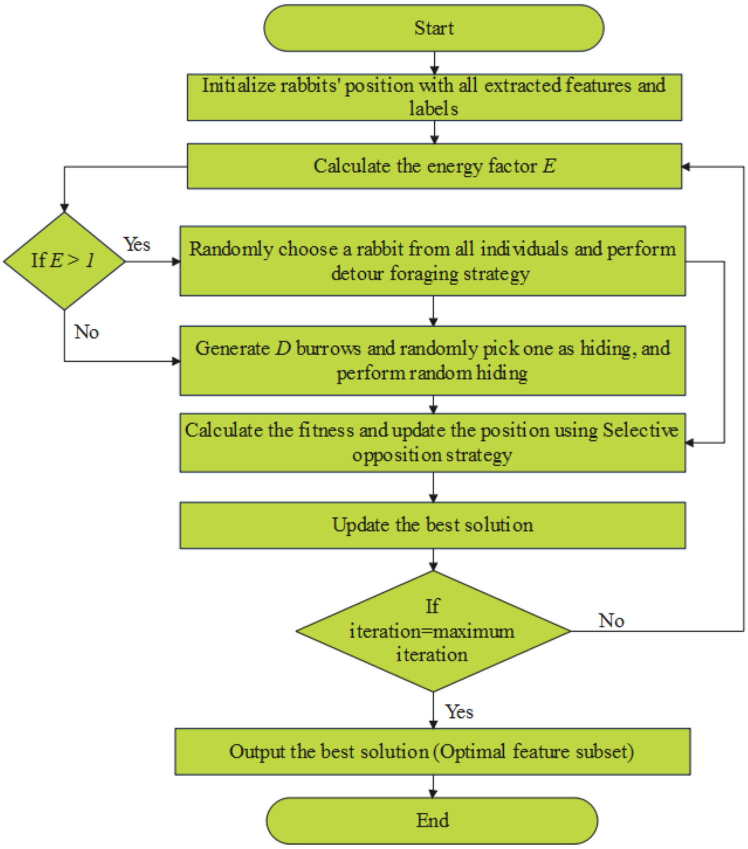


**FIGURE 6.** Flowchart for SOARO.

The main contribution of Auto encoder is the noise reduction of which used to enhance the classification. Additionally, the error rate is reduced by using backpropagation during the classification. Therefore, the AE provides the precise classification among the different arrhythmia classes such as normal beat, supraventricular ectopic beat, ventricular ectopic beat, fusion beat and unknown beat. The classified outputs is given to SHAP for performing the interpretation. SHAP is a game theoretic way of defining the classifier's performance. SHAP uses an additive feature imputation model in that output is denoted as a linear accumulation of input values for generating an interpretable model.

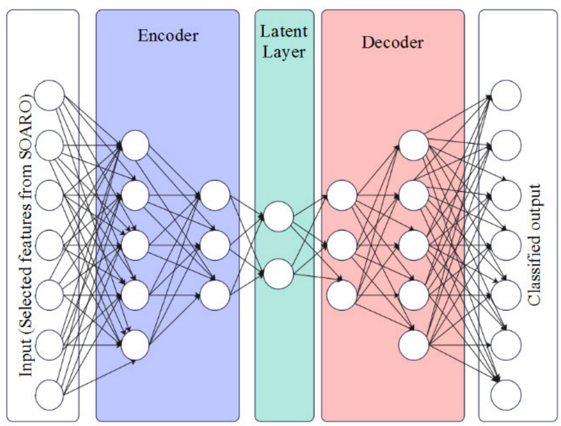


**FIGURE 7.** Architecture of AE.

### *F. IoMT FRAMEWORK FOR ARRHYTHMIA CLASSIFICATION*

The IoMT framework with artificial intelligence is developed for developing the application and additional processing. The system has two units in that first unit referred as front end used PHP language that deploys and run web service to manage the signals from the mobile pad or user device for processing the unit i.e., google Tensor flow cloud platform in backend for computation purposes. This research considers the Hospital Management System (HMS) with three different access from Admin, Doctor and User. In general, Admin has the information about the patients who are visiting the hospital for different purposes such as Dermatology, Gynaecology, Cardiology, Oncology and others. The screenshot of HMS for Admin is shown in Fig. 8. Fig. 8 shows that peoples who are visiting for Cardiology is comparatively more than other medical related issues.

In Cardiology, the patients are visiting for different diseases such as heart attack, valve congestion, heart failure, arrhythmia and others. These details are accessed by the

**Algorithm 1** Pseudo Code for Optimum Feature Selection Using SOARO

```
Input: All features and labels
Compute fitness using (31)
for i = 1 : P do
    if z_i ≠ z_ibest then
        for j = 1 : D do
            Compute difference distance of the jth
             dimension using (28).
             if dd_j < TS then
                 Compute far dimension (D_f) and
                 far distance dimensions.
             else
                 Compute close dimension (D_c) and
                 close distance dimensions.
             end if.
        end for
        Add overall dd_j,
            Compute correlation (src) using (29).
            if src ≤ 0 and size (D_f) > size (D_c) then
                Update the solution using (30).
            end if
    end if
    if Fitness (z⃗_i (t + 1)) > z⃗_ibest
                z⃗_ibest = z⃗_i (t + 1)
    end if
end for
Output: Selected features.
```

Doctor whereas the screenshot of HMS for Doctor is shown in Fig. 9. Fig. 9 shows that the patients who are visiting the hospital with arrhythmia is 40% which is high when compared to other diseases. A sample screenshot for the user who is having the arrhythmia is shown in Fig. 10.

The SOAP protocol used by web services to transfer the user's data from device to other medium and service was defined using the web-based description language. The second portion of the SOARO-AE has the responsibility to process the received data and classify the arrhythmia using Python. The user has choice to accomplish the data-processing for broadcasting the signal for configuring the system, when it is linked with IoMT. This developed SOARO-AE with IoMT communication has the following benefits: 1) It is used in remote locations, 2) the acquired medical data is broadcasted between the Doctors and 3) an entire medical history is stored for medical purposes. Therefore, the SOARO-AE can be used in wide range because of aforementioned applications.

## V. SIMULATION RESULTS

This section shows the classification of arrhythmia with IoMT using the proposed method whereas the python 3 is used to design and simulate the SOARO-AE method. The system used for the implementation is configured with 8 GB RAM and i5 processor with 2.2 GHz. The dataset used to analyse the proposed method is MIT-BIH arrhythmia dataset where 30% data taken for testing and 70% taken for training purpose. Moreover, the SOARO-AE method is also analysed on CPSC 2018 dataset [43] which has 9 classes such as Normal, First-degree atrioventricular block (I-AVB), Atrial fibrillation (AF), Premature ventricular contraction (PVC), Right bundle branch block (RBBB), Left bundle branch block (LBBB), Premature atrial contraction (PAC), ST-segment depression (STD), ST-segment elevated (STE). The data of MIT-BIH arrhythmia is collected using 2 electrodes while the CPSC 2018 dataset uses 12 electrodes for collecting the data. Similar to MIT-BIH arrhythmia dataset, 30% data taken for testing and 70% taken for training purpose from CPSC 2018 dataset.

### A. EVALUATION METRICS

The SOARO-AE is evaluated in terms of accuracy, sensitivity, specificity, recall and F1-Measure which are expressed in (32)-(36).

$$Accuracy = \frac{TP + TN}{TN + TP + FN + FP} \times 100 \tag{32}$$

$$Precision = \frac{TP}{TP + FP} \times 100 \tag{33}$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100 \tag{34}$$

$$Specificity = \frac{TN}{TN + FP} \times 100 \tag{35}$$

$$F1 - measure = \frac{2TP}{2TP + FP + FN} \times 100 \tag{36}$$

where, *TP* is true positive; *TN* is the true negative; *FP* is a false positive and *FN* is a false negative.

### B. PERFORMANCE ANALYSIS OF SOARO-AE METHOD

A different optimization-based feature selection approaches such as Whale Optimization Algorithm (WOA), Butterfly Optimization Algorithm (BOA), Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), Modified Artificial Hummingbird Algorithm (MAHA) and ARO are considered for analysing the performances of SOARO. The performance of SOARO with WOA, BOA, PSO, GWO, MAHA and ARO for different population size is shown in the Fig. 11. From this analysis, it is found that the SOARO with population size 40 provides better performances.

The fitness graph for SOARO with WOA, BOA, PSO, GWO, MAHA and ARO is shown in the Fig. 12. The confusion matrix for the developed SOARO-AE is shown in the Fig. 13. This confusion matrix shows the classification of actual and predicted classes of AE with selected features. The receiver operating characteristic curve namely ROC curve is shown in the Fig. 14 which shows the balancing among the different classes while performing the classification.

The time and complexity analysis of SOARO with WOA, BOA, PSO, GWO, MAHA and ARO analysed in MIT-BIH

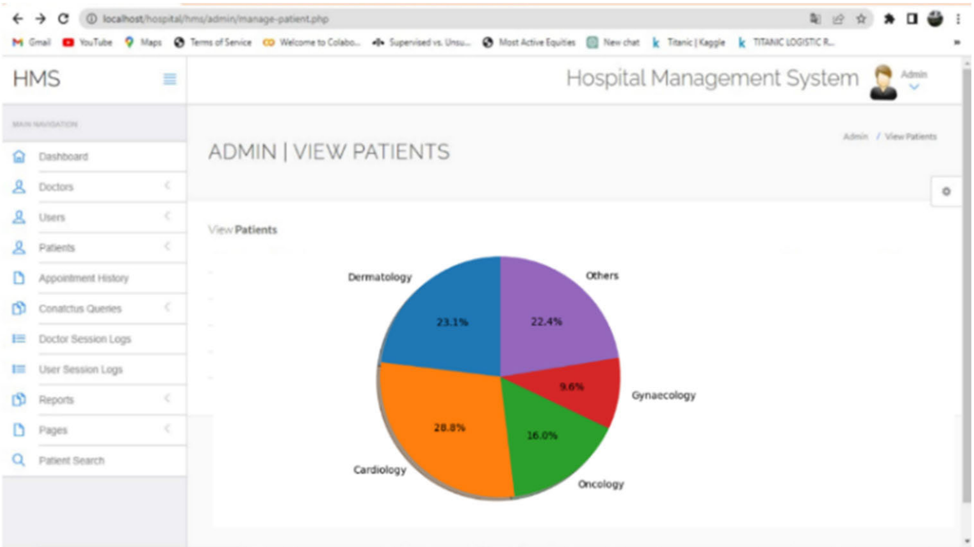


FIGURE 8. Screenshot of HMS for admin.

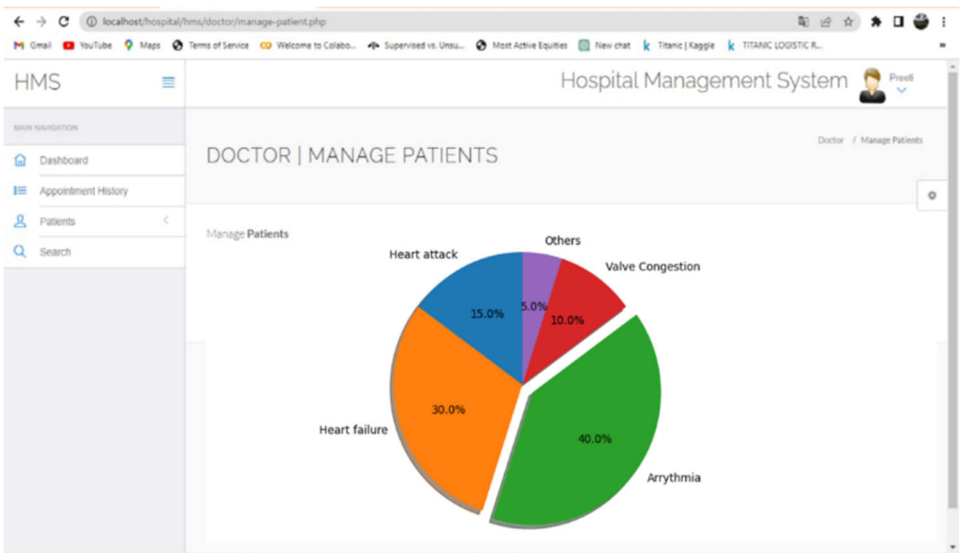


FIGURE 9. Screenshot of HMS for doctor.

arrhythmia dataset is shown in the Table 1. Here, the complexity is analysed in terms of memory. The changes in the proximity dimension of rabbits in the population is used to obtain the faster convergence that helps to minimize the time and memory than the WOA, BOA, PSO, GWO, MAHA and ARO. The SO supports the assists for obtaining the optimal solution during the development phase by altering the proximity dimension of various rabbits.

The performances of SOARO-AE method is analysed for different classifiers and different feature selection approaches. Here, the performances are analysed with MIT-BIH arrhythmia dataset and CPSC 2018 dataset. The different classifiers considered for analysing the AE are Sparse Auto Encoder (SAE), CNN, Multi Class – SVM (MC-SVM) and Recurrent Neural Network (RNN). Further, the performances are analysed for classifier with all features and selected features using SOARO. The analysis of AE with different

TABLE 1. Time and complexity analysis.

| Feature selection approaches | Time (s) | Memory (KB) |
|---|---|---|
| WOA | 4.32 | 440 |
| BOA | 4.09 | 308 |
| MAHA | 2.95 | 244 |
| PSO | 4.51 | 470 |
| GWO | 4.45 | 463 |
| ARO | 2.84 | 241 |
| SOARO | 1.91 | 153 |

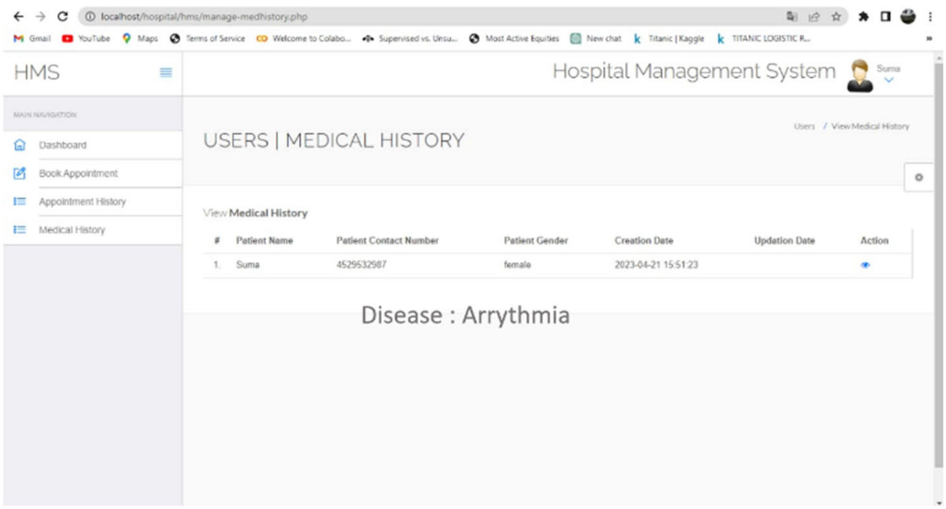


**FIGURE 10.** Screenshot of HMS for user.

**TABLE 2.** Analysis of AE with different classifiers for MIT-BIH arrhythmia dataset.

| Features | Classifiers | Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision (%) | F1-Measure (%) |
|---|---|---|---|---|---|---|
| All features | RNN | 89.51 | 90.23 | 90.84 | 88.21 | 88.61 |
| | CNN | 92.26 | 92.07 | 91.10 | 92.46 | 91.48 |
| | MC-SVM | 92.79 | 92.00 | 92.48 | 92.60 | 92.14 |
| | SAE | 93.51 | 92.25 | 93.90 | 92.33 | 92.53 |
| | AE | 95.07 | 94.98 | 94.49 | 95.16 | 94.85 |
| Selected features | RNN | 92.34 | 91.12 | 91.83 | 92.98 | 92.41 |
| | CNN | 95.32 | 93.67 | 94.66 | 94.59 | 94.59 |
| | MC-SVM | 95.63 | 94.71 | 95.04 | 94.81 | 95.76 |
| | SAE | 96.34 | 95.14 | 95.35 | 96.18 | 96.12 |
| | AE | 98.89 | 99.38 | 98.47 | 99.15 | 99.41 |

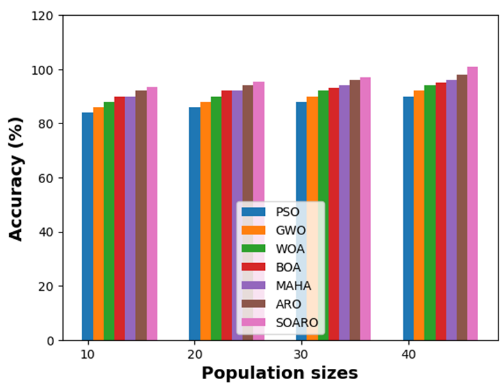


**FIGURE 11.** Comparison of feature selection for different population size.

classifier performances for MIT-BIH arrhythmia and CPSC 2018 datasets are shown in the Tables 2 and 3 respectively. Moreover, the example graph of classifiers analysed in MIT-BIH arrhythmia dataset for all features and selected features are shown in Figs. 15 and 16 respectively. Further, the time and complexity analysis for per signal from MIT-BIH arrhythmia dataset is shown in the Table 4. This analysis shows that the AE achieves the better performance than the SAE, CNN, MC-SVM and RNN, even it analysed with all features and selected features using SOARO. For example, the accuracy of AE analysed in MIT-BIH arrhythmia dataset for all features is 95.07% whereas the RNN obtains as 89.51%, CNN obtains as 92.26%, MC-SVM obtains as 92.79% and SAE obtains as 93.51%. On the contrary, the AE with selected features offers the accuracy of 98.89% which is higher than the AE with all features i.e., 95.07%. The backpropagation used in the AE is used to minimize the error rate which used to improve the classification. Moreover, the SOARO used to select deep optimal features that helps to avoid the misclassification.

The analysis of statistical hypothesis testing is utilized for discovering whether the outcomes are statistically significant or not. McNemar test is a statistical evaluation for analyzing the substantial difference of the two classifier's performance. In this analysis, the classifier SAE is taken, because it has next higher performance compared to the AE used in proposed research. Consider, the AE is method A and SAE is method B for analyzing the McNemar test. The ChiSqure ($X^2$) is computed with degree of freedom 1 using the equation (37).

$$X^2 = \frac{(|m_{AB} - m_{BA}| - 1)^2}{m_{AB} + m_{BA}} \tag{37}$$

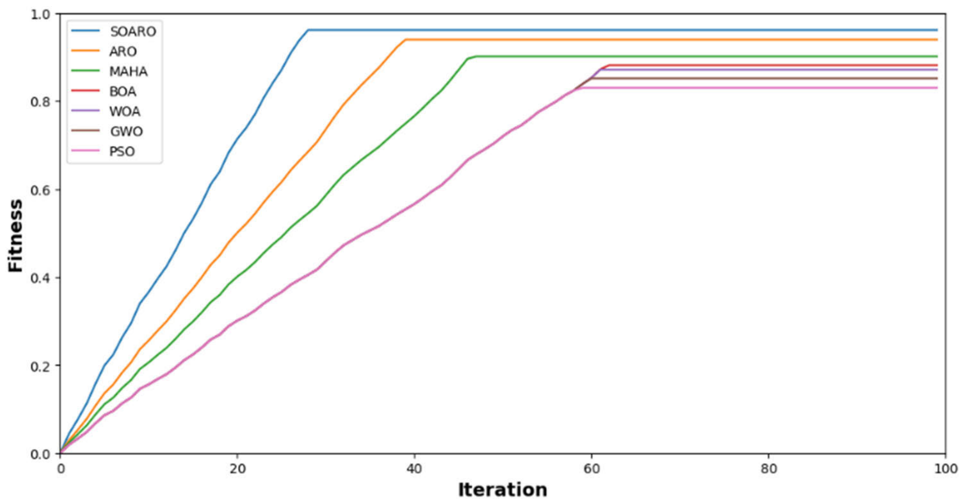


**FIGURE 12.** Fitness graph.

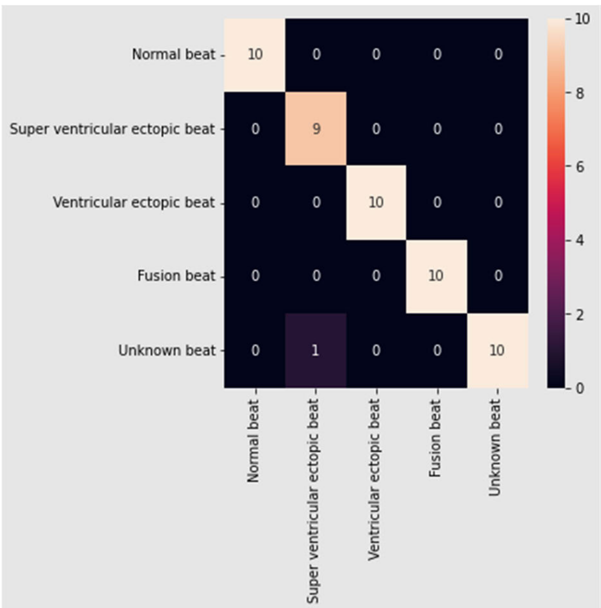


**FIGURE 13.** Confusion matrix for SOARO-AE.

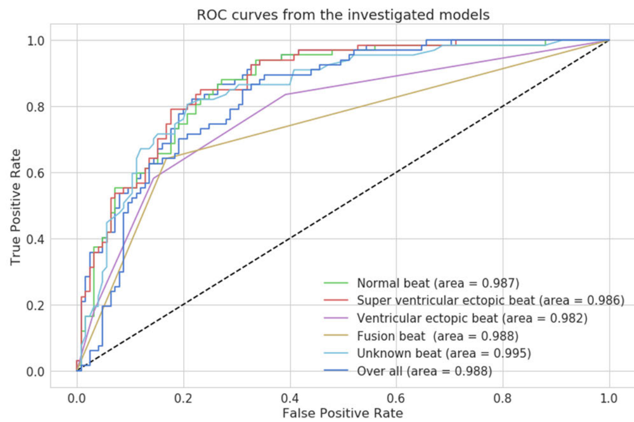


**FIGURE 14.** ROC curve for SOARO-AE.

where, $m_{AB}$ is the samples misclassified by A but precisely classified by B and $m_{BA}$ is the samples misclassified by B but precisely classified by A.

If the computed value is less than 0.05 or higher than 3.85, it denotes that the classifier avoids the null hypothesis. The values of $X^2$ for MIT-BIH arrhythmia and CPSC 2018 datasets are 14.79 and 15.06 that represents it clearly avoids the null hypothesis. Hence, the performance variation of the methods A and B is statistically significant.

In this research, a SHAP model is used for interpreting the classified outputs from the AE. Figs. 17 and 18 shows the interpreted outputs for a sample from MIT-BIH arrhythmia and CPSC 2018 datasets respectively.

The SOARO is also analysed with different feature selection approaches such as Whale Optimization Algorithm (WOA), Butterfly Optimization Algorithm (BOA), MAHA, PSO, GWO and ARO. Table 5 and 6 shows the performance comparison of SOARO with WOA, BOA, MAHA, PSO, GWO and ARO for MIT-BIH arrhythmia and CPSC 2018 datasets. An example graph of SOARO with WOA, BOA, MAHA, PSO, GWO and ARO for MIT-BIH arrhythmia is shown in Fig. 19. The accuracy of SOARO for MIT-BIH arrhythmia is 98.89% whereas the WOA obtains as 90.97%, BOA obtains as 92.85%, MAHA obtains as 95.08%, PSO obtains as 88.05%, GWO obtains as 89.18% and ARO obtains as 95.19%. From the analysis, it is found that the SOARO achieves better performance than the WOA, BOA, MAHA, PSO, GWO and ARO.

Moreover, the accuracy and sensitivity values are used for comparing the optimization approaches used for feature selection based on the statistical analysis. For this purpose, a nonparametric statistical test i.e., Friedman test is used

**TABLE 3.** Analysis of AE with different classifiers for CPSC 2018 dataset.

| Features | Classifiers | Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision (%) | F1-Measure (%) |
|---|---|---|---|---|---|---|
| All features | RNN | 89.29 | 89.52 | 89.33 | 89.68 | 89.13 |
| | CNN | 90.97 | 91.84 | 90.43 | 90.41 | 91.80 |
| | MC-SVM | 91.24 | 92.06 | 91.46 | 92.90 | 92.12 |
| | SAE | 92.65 | 92.53 | 93.83 | 92.70 | 92.90 |
| | AE | 95.11 | 95.27 | 95.84 | 95.00 | 95.77 |
| Selected features | RNN | 91.83 | 92.83 | 92.39 | 92.84 | 91.74 |
| | CNN | 95.13 | 95.16 | 96.08 | 96.89 | 95.65 |
| | MC-SVM | 96.51 | 96.06 | 96.15 | 96.51 | 95.92 |
| | SAE | 97.28 | 96.33 | 97.24 | 97.26 | 96.61 |
| | AE | 98.24 | 98.47 | 99.03 | 98.67 | 98.79 |

**TABLE 4.** Time and complexity analysis.

| Classifiers with selected features | Time (s) | Memory (KB) |
|---|---|---|
| RNN | 0.87 | 226 |
| CNN | 0.76 | 215 |
| MC-SVM | 0.30 | 186 |
| SAE | 0.12 | 145 |
| AE | 0.09 | 112 |

**TABLE 5.** Analysis of SOARO with different feature selection approaches for MIT-BIH arrhythmia dataset.

| Feature selection approaches | Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision (%) | F1-Measure (%) |
|---|---|---|---|---|---|
| WOA | 90.97 | 89.75 | 89.24 | 90.18 | 90.31 |
| BOA | 92.85 | 93.32 | 93.69 | 92.39 | 93.42 |
| MAHA | 95.08 | 96.18 | 95.10 | 95.59 | 96.55 |
| PSO | 88.05 | 87.98 | 87.20 | 87.75 | 87.08 |
| GWO | 89.18 | 89.50 | 88.83 | 89.86 | 88.93 |
| ARO | 95.19 | 96.90 | 95.21 | 95.21 | 96.74 |
| SOARO | 98.89 | 99.38 | 98.47 | 99.15 | 99.41 |

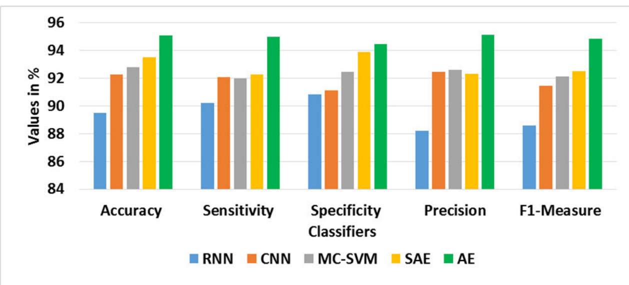


**FIGURE 15.** Graph of different classifiers with all features for MIT-BIH arrhythmia dataset.

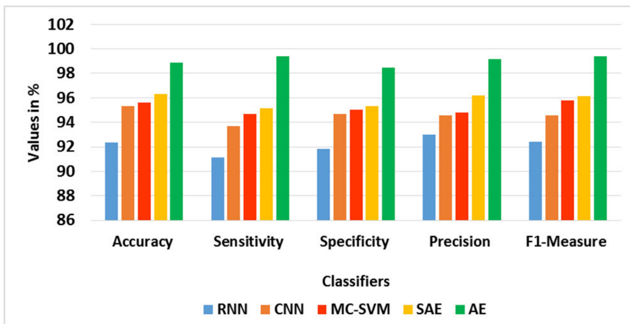


**FIGURE 16.** Graph of different classifiers with selected features for MIT-BIH arrhythmia dataset.

in this research. This test utilizes the ranks of data instead of the data itself and it evaluates the null hypothesis which the column effects are all same. Specifically, all the optimization algorithm used to do the feature selection in this research. This test returns the probability of achieving the observed sample outcome ($p$-value) in the scalar value in the range [0, 1]. In general, the smaller values of $p$ avoids the null hypothesis. The Friedman test to the accuracy and sensitivity values to the values of Tables 5 and 6 for MIT-BIH arrhythmia and CPSC 2018 datasets respectively. The values of $p$ is 0.0043 and 0.0045 for MIT-BIH arrhythmia and CPSC 2018 datasets are computed using Friedman test. Therefore, the $p$-value shows that the SOARO has better performance than the other approaches such as WOA, BOA, MAHA, PSO, GWO and ARO in statistic significant manner.

### C. COMPARATIVE ANALYSIS

The existing researches such as C-LSTM [17], DL-LAC-CNN [18] CNN-DNN [19], MC-ECG [26], FC [29] and MEAHA-CNN [31] are used to evaluate the SOARO-AE method. Here, the comparison is provided for MIT-BIH arrhythmia and CPSC 2018 datasets. For MIT-BIH arrhythmia dataset, the comparative analysis of the SOARO-AE with C-LSTM [17], DL-LAC-CNN [18], CNN-DNN [19], FC [29] and MEAHA-CNN [31] is shown in Table 7. The accuracy graph of C-LSTM [17], DL-LAC-CNN [18], CNN-DNN [19], FC [29], MEAHA-CNN [31] and SOARO-AE for MIT-BIH arrhythmia dataset is shown in Fig. 20. For CPSC 2018 arrhythmia dataset, the comparative analysis of

**TABLE 6.** Analysis of SOARO with different feature selection approaches for CPSC 2018 dataset.

| Feature selection approaches | Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision (%) | F1-Measure (%) |
|---|---|---|---|---|---|
| WOA | 91.56 | 90.63 | 91.96 | 90.28 | 91.24 |
| BOA | 93.72 | 93.67 | 93.87 | 93.06 | 93.70 |
| MAHA | 93.88 | 94.24 | 94.69 | 94.53 | 94.22 |
| PSO | 88.42 | 87.31 | 87.31 | 88.41 | 88.61 |
| GWO | 90.38 | 89.95 | 89.32 | 89.18 | 90.71 |
| ARO | 94.22 | 95.19 | 95.85 | 94.40 | 95.25 |
| SOARO | 98.24 | 98.47 | 99.03 | 98.67 | 98.79 |

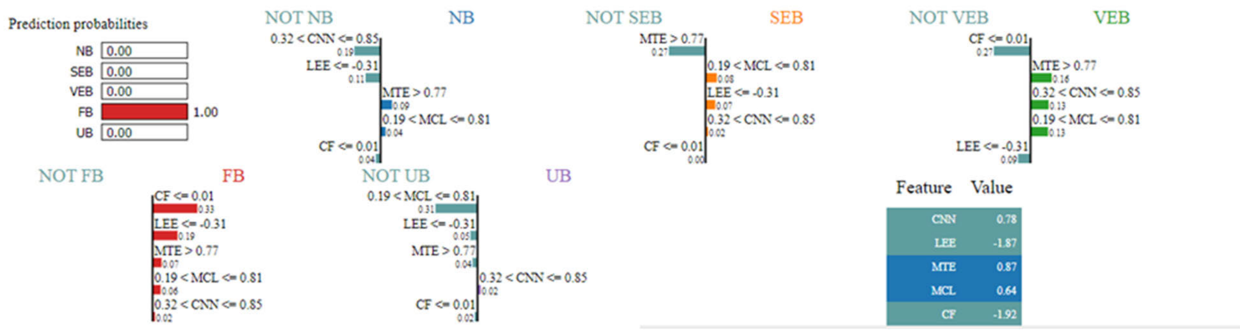


**FIGURE 17.** Interpretation using SHAP for a sample of MIT-BIH arrhythmia.

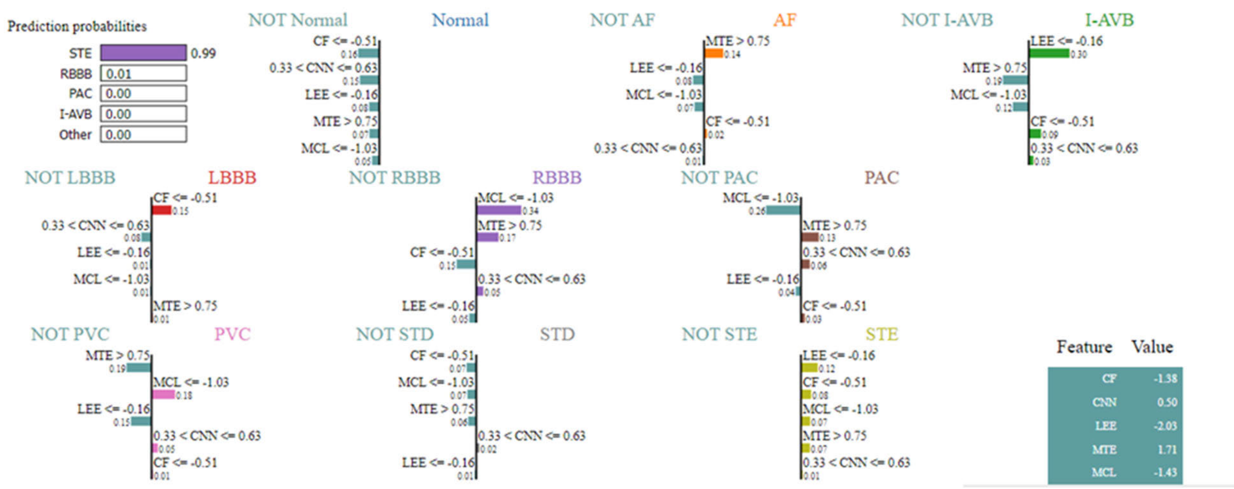


**FIGURE 18.** Interpretation using SHAP for a sample of CPSC 2018.

the SOARO-AE with MC-ECG [26] is shown in Table 8. This analysis shows that the SOARO-AE outperforms well when compared to the C-LSTM [17], DL-LAC-CNN [18], CNN-DNN [19], MC-ECG [26], FC [29] and MEAHA-CNN [31]. For example, the accuracy of SOARO-AE for MIT-BIH arrhythmia dataset is 98.89% whereas the C-LSTM [17] obtains as 96.16%, DL-LAC-CNN [18] obtains as 94.07%, CNN-DNN [19] obtains as 97.008%, FC [29] obtains as 95.81% and MEAHA-CNN [31] obtains as 98.87%. The optimal selection of features using SOARO is used to improve the classification using AE.

## VI. DISCUSSION

This section delivers the brief discussion about the results obtained from the SOARO-AE for ensuring the classification of arrhythmia with IoMT based patient monitoring. At first, the results of SOARO-AE are analysed with different classifiers and optimization based feature selection approaches. The performances are analysed for two different datasets such as MIT-BIH arrhythmia and CPSC 2018 datasets. The results shows that the SOARO-AE provides better performance than the SAE, CNN, RNN, MC-SVM, MAHA, PSO, GWO, WOA, BOA and ARO. For example, the accuracy of SOARO-AE for CPSC 2018 is 98.24% which is high when compared to the SAE, CNN, RNN, MC-SVM, MAHA, PSO, GWO, WOA, BOA and ARO. Further, the SOARO-AE is compared with the C-LSTM [17], DL-LAC-CNN [18] CNN-DNN [19], MC-ECG [26], FC [29] and MEAHA-CNN [31] in comparative analysis section. The SOARO-AE outperforms well than the all the existing approaches. For example, the accuracy of SOARO-AE for MIT-BIH arrhythmia dataset is 98.89% which is high than C-LSTM [17],

**TABLE 7. Comparison of SOARO-AE for MIT-BIH arrhythmia dataset.**

| Performances | C-LSTM [17] | DL-LAC-CNN [18] | CNN-DNN [19] | FC [29] | MEAHA-CNN [31] | SOARO-AE |
|---|---|---|---|---|---|---|
| Accuracy (%) | 96.16 | 94.07 | 97.008 | 95.81 | 98.87 | 98.89 |
| Sensitivity (%) | 93.86 | NA | 97.008 | 69.20 | NA | 99.38 |
| Specificity (%) | 91.45 | NA | NA | 94.56 | NA | 98.47 |
| Precision (%) | NA | 90.7 | 97.011 | NA | NA | 99.15 |
| F1-Measure (%) | NA | 91.75 | 97.009 | 71.56 | NA | 99.41 |

**TABLE 8. Comparison of SOARO-AE for CPSC 2018 dataset.**

| Performances | MC-ECG [26] | SOARO-AE |
|---|---|---|
| Precision (%) | 84.62 | 98.67 |

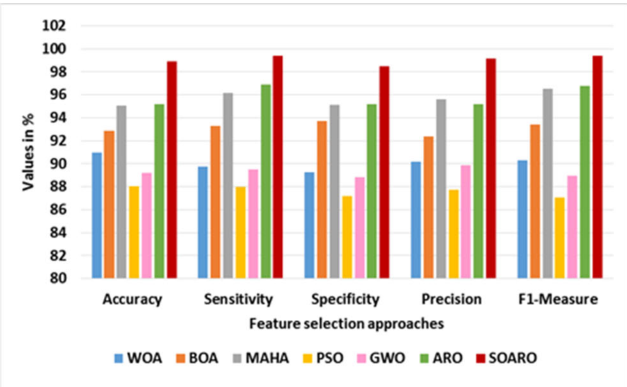


**FIGURE 19. Graph of different feature selection approaches for MIT-BIH arrhythmia dataset.**

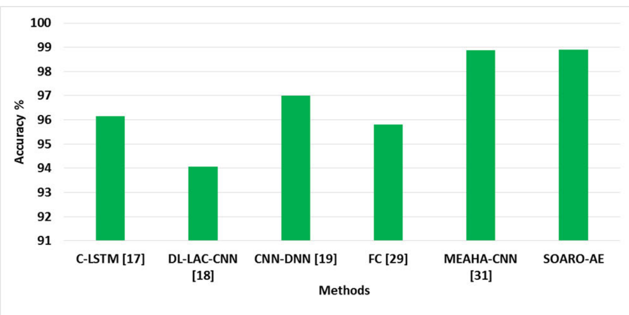


**FIGURE 20. Comparison of accuracy for MIT-BIH arrhythmia dataset.**

DL-LAC-CNN [18], CNN-DNN [19], FC [29] and MEAHA-CNN [31]. In this research, the SOARO based feature selection is used for removing the redundant features from the overall feature set that helps to avoid the overfitting issue and enhances the classification. The MIT-BIH arrhythmia dataset has both the labelled and unlabelled samples (i.e., unknown beat) that leads to create impact in overall classification performances. If these unlabelled samples are selected, there is a possibility of returning higher rate of false positives and lesser precision during the classification. These unlabelled data creates the issue of data imbalance which leads to the biased model performance, as the classifier favors to the majority class. This biased classification affects overall accuracy during Arrhythmia identification.

## VII. CONCLUSION

With the continuous expansion of IoMT, it becomes the suitable to perform the remote monitoring of Arrhythmia. In this research, the SOARO based feature selection is done to choose deep optimal features for improving the classification. The IoMT incorporated in this SOARO-AE is used to monitor the patients who are having arrhythmia. The EMD is utilized in this research for denoising the ECG signal. Next, different categories of features such as time, time-frequency, entropy, nonlinearity and deep features from ResNet-50 are extracted from ECG signal. Next, the selected optimal features from SOARO are given to AE to perform the Arrhythmia classification. From the results, it is concluded that the SOARO provides better performance than the C-LSTM, DL-LAC-CNN, CNN-DNN and MC-ECG, FC and MEAHA-CNN. The accuracy of SOARO-AE is 98.89% which is high when compared to the C-LSTM, DL-LAC-CNN, CNN-DNN, FC and MEAHA-CNN. In future, a hybrid optimization-based feature selection can be performed and issue of data imbalance can be avoided for improving the classification performances.

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