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SQUIRREL SEARCH-BASED OPTIMAL FEATURE EXTRACTION WITH BI-LSTM FOR THE ARRHYTHMIA CLASSIFICATION USING ECG

SHAIK MUNAWAR[1], GEETHA A[2], SRINIVAS KONDA[3]

[1] Computer Science and Engineering, Annamalai University, Tamil Nadu, India.
[2] Computer Science and Engineering, Annamalai University, Tamil Nadu, India.
[3] Computer Science and Engineering, CMR Technical Campus, Telangana, India
E-mail: [1]shaikmunawar215@gmail.com, [2]aucsegeetha@yahoo.com, [3]phdknr@gmail.com

ABSTRACT

Electrocardiogram (ECG) arrhythmia classification seeks more attention in the research areas for preventing and diagnosing cardiovascular diseases. The conventional approaches related to arrhythmia classification have achieved reasonable performance on the detection of diverse heart scenarios particularly when processing with the imbalanced datasets. Recently, deep learning shows an enhanced performance in the area of healthcare industry for extracting the high level of abstract features in an automatic way to reduce time consumption and avoid manual effort. Many researchers have developed deep learning-aided methods for detecting the arrhythmia with the help of ECG signals; however, it fails to ensure the accurate classification. Hence, this paper plans to develop the arrhythmia classification using ECG signals by the intelligent technology. Initially, the data is gathered from online sources. The gathered data undergo pre-processing using noise removal, artifacts removal, and peak detection techniques. From the pre processed signals, the features are extracted using the "Mel Frequency Cepstral Coefficients (MFCC), spectral features, and Short Time Fourier Transform (STFT)". As the extracted feature length is lengthy, significant features are extracted in the optimal feature extraction step using the Squirrel Search Algorithm (SSA). These optimally extracted features are given to the final classification step, where "Bi-directional Long Short Term Memory (Bi LSTM)" classify the heartbeats in a more efficient and accurate manner into 5 prominent classes such as "Normal Sinus Rhythm (N), Left Bundle Branch Block (LBBB or L), Right Bundle Branch Block (RBBB or R), Premature Ventricular Contraction (V), and Atrial Premature Beat (A)" that determines the types of arrhythmia present. The comparison illustrates the success of the proposed ECG classification model.

Keywords: *Electrocardiogram; Arrhythmia Classification; Mel Frequency Cepstral Coefficients; Spectral Features; Short Time Fourier Transform; Optimal Feature Selection; Squirrel Search Algorithm; Bi-directional Long Short Term Memory*

1. INTRODUCTION

Arrhythmia is considered to be a collection of diseases related to the cardiovascular system, which may occur on its own ability [1]. The arrhythmia detection is mostly relied on the ECG that is known as the recent medical tool used to capture the cardiac recovery, excitability, and transmission process. The irregular heart rhythms are automatically detected through ECG signals, which is said to be a vital task in an automated cardiovascular disease diagnosis [2]. ECG is broadly accessed as the tool for diagnosing the arrhythmia in the clinical areas as it is inexpensive and noninvasive in nature. It is used for recording the electrical activities of the heart for a certain time using electrodes that are associated with the skin surface. ECG-based automatic arrhythmia detection helps the doctors regarding the clinical applications and also ensured with effective monitoring of the ordinary people with the help of wearable devices [3]. However, this automatic arrhythmia detection needs to focus on the accuracy problem, which is considered to be a critical issue.

There have different classes of arrhythmias features based on the peculiar pattern at the time of ECG recordings. This shows that the accurate analysis of ECG samples supports the effective recognition of arrhythmia types [4].On the other hand, the arrhythmias are categorized into two classes named as morphological and rhythmic

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arrhythmias. Here, the occasional existence of an individual irregular heartbeat is termed as morphological arrhythmias and the irregular heartbeats at the continuous pattern are termed as rhythmic arrhythmias. The arrhythmia is mostly distinguished with the normal heartbeats according to its speed and rhyme. Several researchers have classified the arrhythmia based on the origin or through its location on the heart chambers [5]. In the medical applications, the morphological alterations present in the wave frequency of ECG are examined for detecting the arrhythmia type or its abnormalities stage. But, the analyzing process of ECG is not much easy owing to the requirement of accurate interpretation regarding every heart regions of the patients. In addition, the analysis may take hour or days to observe the ECG fluctuations. Also, the human errors may also occur due to the fatigue or inexperience [6]. Hence, an automatic classification of ECG recordings is required with the help of computational approaches for offering the accurate interpretation with minimum bias variations.

Now-a-days, deep learning approaches have revealed better performance when processing with the pattern recognition applications [7]. Most of the researchers have changed their focus towards the ECG classification studies with the support of deep learning-based techniques [8]. Following with the feature extraction from ECG signals, the classification is performed with the help of state-of-the-art classifiers [9]. The above-mentioned studies have shown that a deep neural network able to extract the complex representative features from the data for reducing the dependencies on manual feature extractions and also for generating the end-to-end learning systems, where the input is given as the ECG signals and the output is obtained as the arrhythmia class prediction with the automatic deep feature extraction [10].

The significant intentions of the suggested model are listed as below.

- ❖ To develop an intelligent arrhythmia classification model with the utilization of deep learning approach using the heuristic approach for ensuring the earlier detection of the cardiovascular diseases.
- ❖ To implement the deep learning-based approach for classifying the arrhythmia types with the support of SSA. To get the optimal feature from the concatenated features using the suggested SSA to reduce the complexity of classification process.
- ❖ To validate the effective performance of the suggested model with diverse meta-heuristic and classification approaches.

The further sections are detailed as follows, where the existing works are described in section II and the proposed model is depicted in section III. Similarly, the optimal feature selection is performed in section IV and the classification is conducted in section V. finally, the section VI explains the results of the suggested model and the conclusion is given in section VII.

2. LITERATURE SURVEY

2.1 *Related Works*

Sections In 2019, Huang *et al.* [11] have suggested an deep learning network. The time-domain ECG signals were classified into five different types of the heartbeats by transforming them into the time-frequent spectrograms using an efficient Fourier transform approach. Then, the deep learning-based approach was used for classifying and identifying the arrhythmia types. Finally, it was evaluated that the suggested model has provided improved performance regarding the classification accuracy independent of any manual ECG pre-processing. In 2021, Zhang *et al.* [12] have suggested fusion network for classifying the arrhythmia by developing the multi-loss optimization of multi-lead ECG. The proposed model was enclosed with three components, in which the diverse lead-particular branches to learn the multi-lead ECG diversity, cross-lead features concatenation through the combination of output features from all types to learn the development of multi-lead ECG and multi-loss co-optimization was performed for all types and the concatenated network. The simulation results have shown the proposed model has attained better classification performance on arrhythmia.

In 2021, Sharma *et al.* [13] have presented a effective combined approach to classify the ECG samples into the significant arrhythmia classes for detecting the abnormalities in the heartbeat. The classification was performed by eliminating the inherent noise presented in the ECG signals with the help of wavelet transformation technique. The machine learning approach was used to classifying the ECG signals into five different classes with the help of training information. The ECG classification model has attained the accurate classification of ECG signals.

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In 2021, Pal *et al.* [14] have suggested a new approach for classifying the heartbeat from the ECG with the utilization of deep learning approach. This automated system was functioned with the procedure of transfer learning approach to acquire the fast and consistent classification performance by training numerous images. The developed system has attained better performance and consistency than the other methods. In 2021, Houssein *et al.* [15] have introduced various descriptors of ECG signals with the help of different feature extraction techniques. Then, the feature selection and classification tasks were performed with machine learning and optimization algorithm for determining the relevant features. The suggested model was trained and detected the four types of abnormal heartbeats and one normal heartbeat. The experimental analysis has carried out and has shown the superior performance of the suggested model.

2.2 Problem Statement

The automated diagnosis of cardiac illness relies heavily on the categorization of ECG data. Deep learning, which has been trained on a large quantity of data, has identified cardiac arrhythmias higher than experienced cardiologists, thanks to recent breakthroughs in artificial intelligence.

Table I lists the features and challenges of traditional arrhythmia classification methods. CNN [11] does not require extra manual pre-processing of the ECG signals and also returns high accuracy and lowest loss. But, it does not combine with various machine learning approaches for detecting the heart rate abnormalities and arrhythmia. MLBF-Net [12] can be used in daily monitoring and clinical applications and has the advantage of light weight and high screening ability. Still, it does not provide a comprehensive arrhythmia classification technique by ECG signals. FFBPNN [13] categorizes the ECG signals in an accurate manner and also enhances the classification strength. Yet, various arrhythmia classes are not included. Transfer learning [14] increases the accuracy and is robust to various arrhythmias. But, it does not improve the performance with consideration of complex applications and real-world problems. MRFO [15] improves the accuracy associated with the classification models and is helpful for the professionals for diagnosing the heart diseases on the basis of the ECG signal. Still, it does not improve the performance by hybridizing MEFO with various improvement strategies or meta heuristic algorithms.

TABLE I : FEATURES AND CHALLENGES OF TRADITIONAL ARRHYTHMIA CLASSIFICATION methods

Author [citation]	**Methodology**	**Features**	**Challenges**
Huang *et al.* [11]	CNN	• It returns high accuracy and lowest loss. • It does not require extra manual pre processing of the ECG signals.	• It does not combine with various machine learning approaches for detecting the heart rate abnormalities and arrhythmia.
Zhang *et al.* [12]	MLBF-Net	• It has the advantage of light weight and high screening ability. • It can be used in daily monitoring and clinical applications.	• A comprehensive arrhythmia classification technique is not provided by ECG signals.
Sharma *et al.* [13]	FFBPNN	• The classification strength is enhanced. • The ECG signals are categorized in an accurate manner.	• It does not include various arrhythmia classes.
Pal *et al.* [14]	Transfer learning	• It is robust to various arrhythmias. • The accuracy is increased.	• The performance is not improved with consideration of complex applications and real-world problems.

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Houssein *et al.* [15]	MRFO	• It is helpful for the professionals for diagnosing the heart diseases on the basis of the ECG signal. • The accuracy associated with the classification models is improved.	• The performance is not improved by hybridizing MEFO with various improvement strategies or meta- heuristic algorithms.

3. DEVELOPING A NOVEL ARRHYTHMIA CLASSIFICATION MODEL WITH ECG SIGNALS USING DEEP LEARNING APPROACH

3.1 Proposed Model and Description

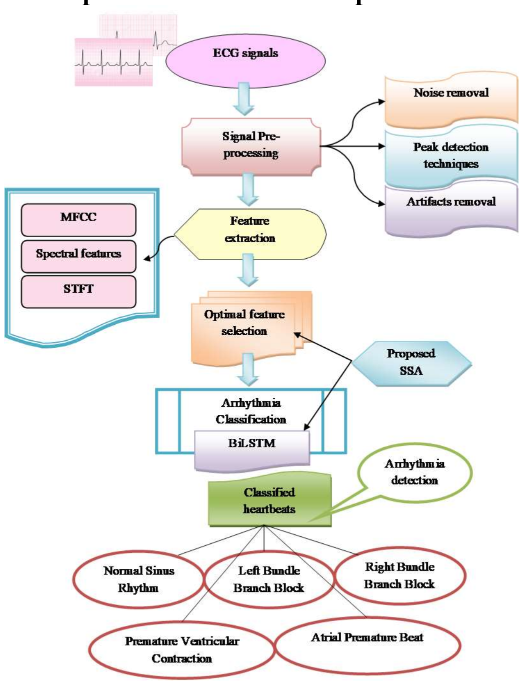

Fig. 1. Architectural diagram of the proposed Arrhythmia Classification Model

The effectiveness of the conventional classification approaches is mainly relied on the extracted features from the dynamic ECG signals that need human labor and expert knowledge [16]. Earlier arrhythmia detection depends on the expertise doctors for interpreting the features of the ECG signals. The accurate diagnosis of the arrhythmia is highly affected by the mental states and environmental factors. Additionally, there is a need of huge amount of ECG signals that are obtained from the monitoring system of the patient for satisfying the recent medical demands with the help of artificial analysis and interpretation. Therefore, an automatic ECG signal-based arrhythmia classification needs to be developed for the increasing the support to the doctors by providing the effective and consistent diagnosis of cardiovascular disease. The diagrammatical view of the suggested arrhythmia classification model is given in **Fig. 1**.

A new arrhythmia classification model is implemented using ECG signals with the involvement of deep learning approach to detect the type of arrhythmia. The ECG signals is collected from the standard datasets, which is pre-processed using noise removal, artifacts removal, and peak detection techniques. The pre-processed signals are used into the MFCC, STFT and spectral features for extracting the signal features. The most significant signal features are selected with the support of proposed SSA. Then, the classification is performed with the Bi-LSTM to categorize the five different classes of heartbeats to identify the type of arrhythmia. Here, the parameters like hidden neurons and epochs are optimized using the SSA for enhancing the classification performance regarding the accuracy and precision.

3.2 Dataset Description of ECG Signal

The ECG signals required for classification of arrhythmia is obtained from two different datasets like "ECG-ID Database and ECG signals (1000 fragments)" that are described as below.

Dataset 1 ("ECG-ID Database"): This dataset is collected from [17]. The dataset is comprised of 310 ECG recordings obtained from the 90 individuals.

Dataset 2 ("ECG signals (1000 fragments)"): this is gathered from [18]. The dataset is enclosed with the ECG recordings of 45 patients with the number of 17 classes.

The collected ECG signals are indicated as ES_d^{ip}, where $d = 1,2,\ldots,D$ and D show the total count of ECG signals.

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4. SSA-BASED OPTIMAL FEATURE SELECTION OF ECG SIGNALS

4.1 SSA-based Optimization

The proposed arrhythmia classification model utilizes the SSA for choosing the best features and optimizing the hidden neurons count and epoch count of the Bi-LSTM. SSA is implemented based on the motivation of the jumping mechanism and gliding strategies of the flying squirrels. Here, the new position of each squirrel is computed in Eq. (19).

$$z_{ac}^{new} = \begin{cases} z_{ac}^{old} + rd_G GC\left(z_{hk}^{old} - z_{ac}^{old}\right) & if\ r_1 \geq PR_{pd} \\ random\ position & others \end{cases}$$
(1)

Here, the gliding constant is indicated by GC and the random function r_1 is determined from the interval $[0,1]$. The new position to the acorn nut trees is decided by Eq. (24).

$$z_{nt}^{new} = \begin{cases} z_{nt}^{old} + rd_G GC\left(z_{ac}^{old} - z_{nt}^{old}\right) & if\ r_2 \geq PR_{pd} \\ random\ position & others \end{cases}$$
(2)

Here, the term r_2 denotes the random function that is determined from the interval $[0,1]$. The new position of the squirrel to the hickory nut tree is formulated in Eq. (25).

$$z_{nt}^{new} = \begin{cases} z_{nt}^{old} + rd_G GC\left(z_{hk}^{old} - z_{nt}^{old}\right) & if\ r_3 \geq PR_{pd} \\ random\ position & others \end{cases}$$
(3)

Here, the term r_3 indicates the random variable from the interval of $[0,1]$. When the summer season arises, all individuals update their position to f_{hk} that is shown in Eq. (4).

$$z_{nt}^{new} = z_L + LEVY(nn) \times (z_U - z_L)$$
(4)

The levy distribution is known to be $LEVY(nn)$. The pseudo code of the proposed BF-SSA is given in Algorithm 1.

Algorithm 1: SSA [19]

Generate the initial population PP and its input parameters

Compute the random locations for a count of flying squirrels

Compute the fitness of the position of every individuals

Arrange the squirrel position according to the fitness

While (stopping condition) do

For $j = 1\, to\, nn_1$

Update the solution using Eq. (1) when $(r_1 \geq PR_{pd})$

End for

For $j = 1\, to\, nn_2$

Update the solution using Eq. (2) when $(r_2 \geq PR_{pd})$

End for

For $j = 1\, to\, nn_3$

Update the solution using Eq. (3) when $(r_3 \geq PR_{pd})$

End for

End while

If $(SE_c^m < SE_{cMIN})$

Relocate the flying squirrel randomly using Eq. (4)

End if

Obtain a best optimal solution

4.2 ECG Signal Pre-processing

The collected ECG signals ES_d^{ip} are used in the pre-processing phase by undergoing noise removal, artifacts removal and by performing the peak detection technique.

Noise removal: ECG signals is comprised of various kinds of electrode motion noise, Electromyo-Graphic (EMG) noise, power line interference and noises-baseline wander noise, which are need to be removed for getting effective features.

Artifacts removal: The unnecessary artifacts in the ECG signals are removed by generating the ECG template. Here, the signals are considered to be low pass filtered, where the artifacts are removed to get the clear signals for the feature extraction.

Peak detection techniques: This technique is used for getting the morphological features such as the location peaks and amplitude and their ranges from the collected ECG signals ES_d^{ip}. The pre-processed ECG signals are denoted by ES_d^{pr}.

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4.3 Feature Extraction

The feature extraction process of the suggested arrhythmia classification model is performed with the pre-processed signals for extracting the MFCC, STFT and spectral features.

MFCC: The pre-processed signals ES_d^{pr} are used in this MFCC feature extraction technique, where the coefficients of Mel frequency ceptrum are attained from the input signals. The coefficients $\Delta MFCC$ of are computed using Eq. (5).

$$\Delta cepm(m) = \alpha \sum_{n=1}^{2} n\left(cepm(m+n) - cepm(m-n)\right)$$
(5)

$$\Delta\Delta cepm(m) = \Delta cepm(m+1) - \Delta cepm(m-1)$$
(6)

Here, the constant is represented as α . According to the Eq. (6), the coefficients $\Delta\Delta MFCC$ are measured. The extracted features of MFCC are denoted as FE_g^{mfcc} .

Spectral features: The extraction of the spectral features like Power Spectral Density (PSD) is required based on the mean PSD, Carried out under the time-frequency analysis, in which
The time-frequency energy density function is shown. The
Variation of the signal frequency is observed in the time-frequency analysis with time that is a non-stationary signal. The extracted features of MFCC are denoted as FE_j^{stft} .The concatenated features from MFCC, spectral features and STFT are indicated as $FE_s^{ex} = \left\{FE_g^{mfcc}, FE_h^{SPF}, FE_j^{stft}\right\}$.

4.4 Optimal Feature Selection

The proposed model is employed with SSA to reduce the feature length of FE_s^{ex} using the proposed SSA. The optimal features are indicated as $FE_{s^*}^{opt}$, where $s^* = 1,2,\cdots,S^*$ and S^* denote the optimal feature count, which are selected using SSA. The main objective of performing the optimal feature selection is to reduce the variance among the features that is given in Eq. (10).

$$F_1 = \underset{\left\{FE_{s^*}^{opt}\right\}}{\arg\max}\left[\frac{1}{\mathrm{var}}\right] \qquad (10)$$

Here, the term var represents the variance among the selected features, which needs to be less.

maximum PSD and PSD Variance of the EEG signals are represented in the below equations.

$$\overline{T} = \frac{\Sigma_{\omega}\, \omega Q(\omega)}{\Sigma_{\omega} Q(\omega)} \quad (7)$$

$$Q_{MAX} = MAX\left(Q(\omega)\right) \quad (8)$$

$$\sigma_t^2 = \frac{\Sigma_{\omega}\left(\omega - \overline{Q}\right)^2 Q(\omega)}{\Sigma_{\omega} Q(\omega)} \quad (9)$$

Here, the terms Q_{MAX} and $\overline{T}$ represents the signal frequency of the maximum power and frequency value at the centered signal power spectrum, respectively. The symbol σ_t^2 denotes the power variations for various frequencies signal. The extracted features of MFCC are denoted as FE_h^{SPF} .

STFT: The signal feature extraction helps to refuse unwanted artifact from the ECG signal and makes it suitable for further processing. The signal feature extraction is

5. BI-LSTM-BASED ARRHYTHMIA CLASSIFICATION WITH OPTIMAL FEATURE SELECTION

5.1. Bi-LSTM-based Heartbeat Classification

The proposed classification model employs Bi-LSTM for classifying the arrhythmia types, where the parameters of the Bi-LSTM such as hidden neurons and epoch are tuned with the help of suggested SSA for improving the classification accuracy and precision using input features $FE_{s^*}^{opt}$.
The Bi-LSTM network provides better performance than LSTM while applying it into the sequential data applications. The proposed model focuses on solving the objective function in terms of maximizing the accuracy and precision of the arrhythmia classification. The aim of the developed model is indicated in Eq. (17).

$$F_2 = \underset{\left\{HN_b^{blstm}, ep_c^{blstm}\right\}}{\arg\min}\left(\frac{1}{acr + prc}\right) (17)$$

Here, the term HN_b^{blstm} and ep_c^{blstm} denotes the hidden neurons and number of epoch of classifiers. The classification accuracy and precision are expressed as acr and prc , respectively.

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6. RESULTS AND DISCUSSIONS

6.1. Experimental Setup

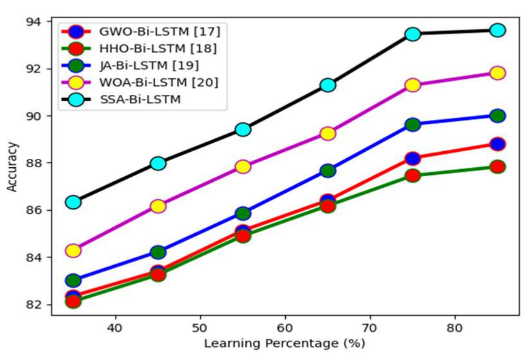
The arrhythmia identification model using ECG signals was developed in Python, and analyzed experimentally. The proposed SSA-Bi-LSTM was analyzed with other algorithms like" Grey Wolf Optimization (GWO) [20], Harris hacks Optimization (HHO) [21], Jaya Algorithm (JA) [22] and Whale Optimization Algorithm (WOA) [23] and classifiers like CNN [11], RNN [8], LSTM [7], and Bi-SLTM [10]".

6.2. Performance Measure

The suggested model is validated through several performance metrics that are acquired from [24].

6.3. Meta-Heuristic Algorithm Analysis

The suggested arrhythmia identifications undergoes meta-heuristic analysis as in Fig 2 at varying learning percentage. The SSA-Bi-LSTM shows 6.12%, 4.2%, 22.3%, and 21.12% improved accuracy than the GWO-Bi-LSTM, HHO-Bi-LSTM, JA-Bi-LSTM and WOA-Bi-LSTM, respectively at the learning percentage as 75. Thus, the overall performance for developed arrhythmia classificationsecures valuable performance than other existing methods.



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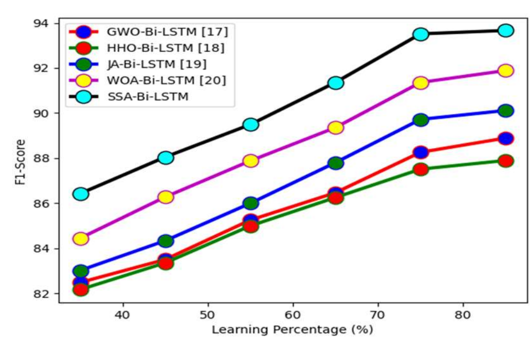

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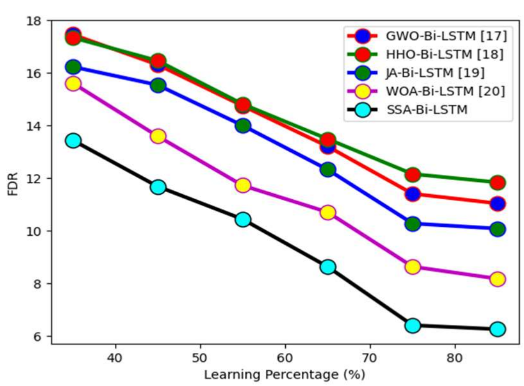

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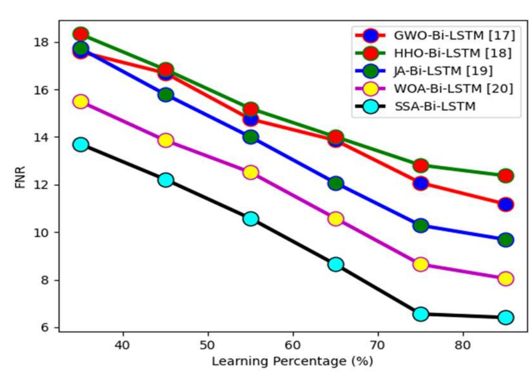

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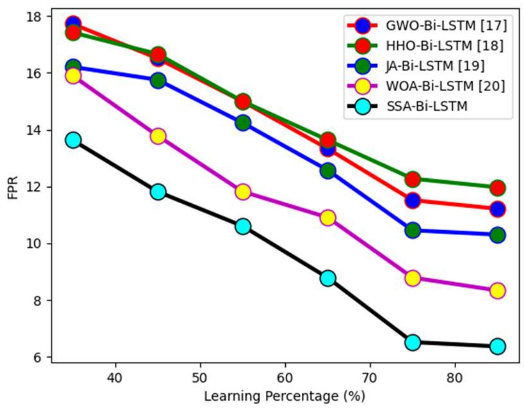

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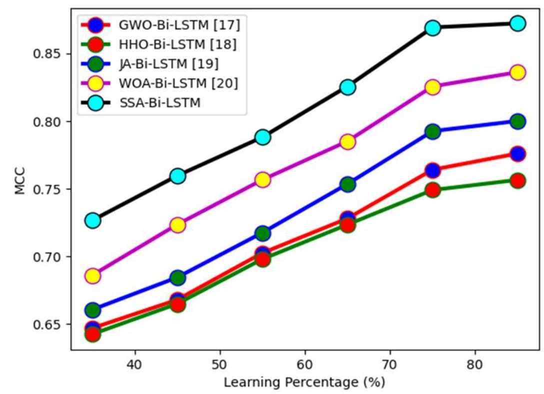

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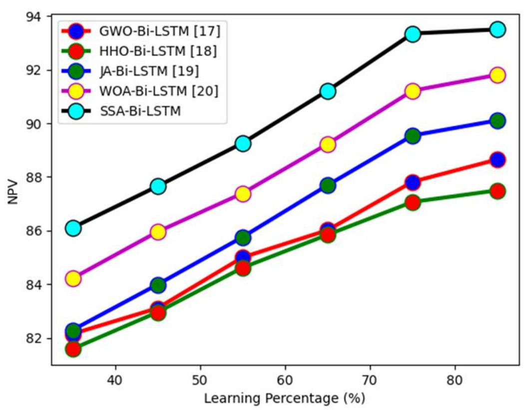

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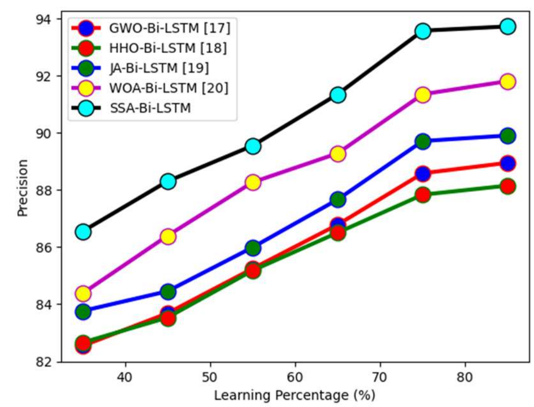

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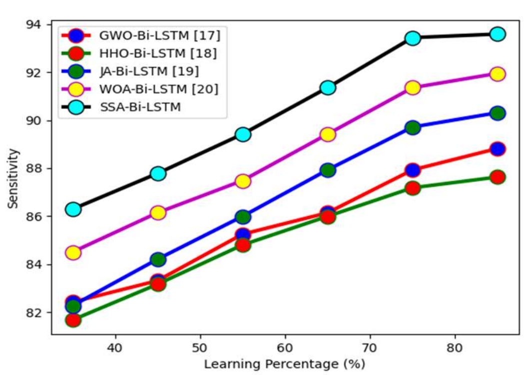

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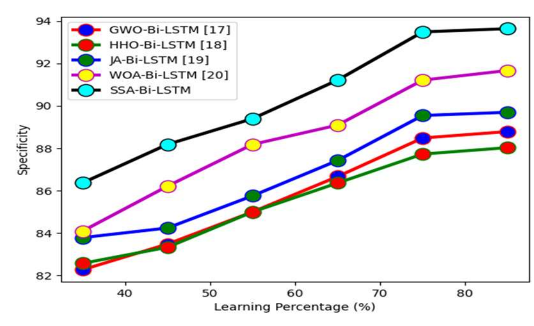

(j)

Fig. 2. Evaluation on proposed arrhythmia classification model in terms of "(a) accuracy, (b) F1-Score, (c) FDR, (d) FNR, (e) FPR, (f) MCC, (g) NPV, (h) precision, (i) sensitivity and (j) specificity"

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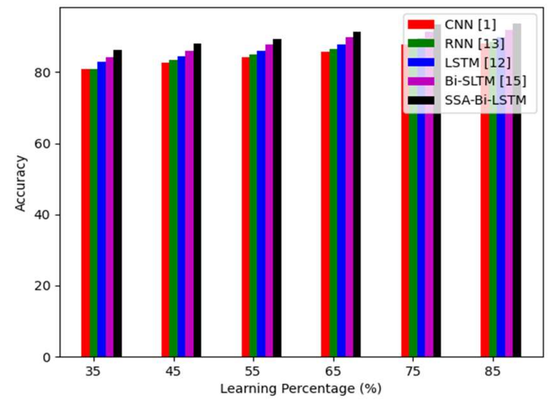
6.4. Classifier Evaluation

The arrhythmia classification model is evaluated by comparing with different classifiers as in Fig 3 at varying learning percentage. The SSA-Bi-LSTM contains 24.3%, 21.25%, 7.78% and 5.43% higher than the "CNN, RNN, LSTM and Bi-SLTM", respectively at the learning percentage of 35 concerning the accuracy. Thus, the SSA-Bi-LSTM for proposed arrhythmia classification model shows higher performance than other conventional methods.



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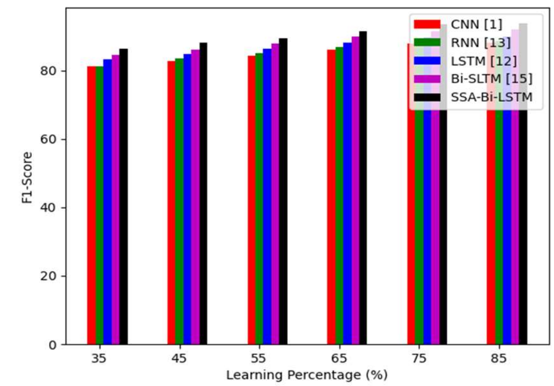

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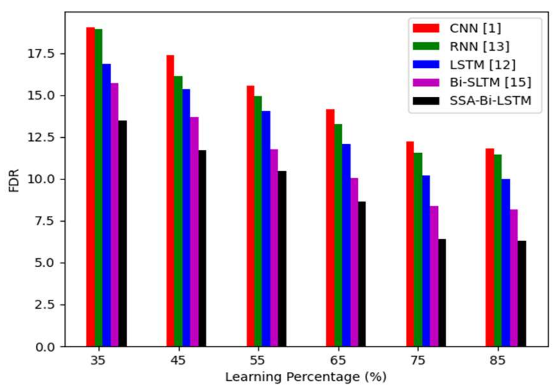

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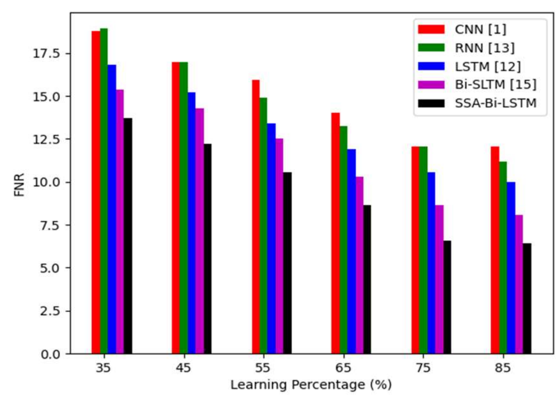

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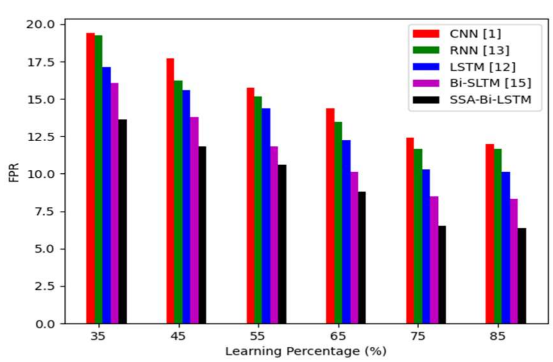

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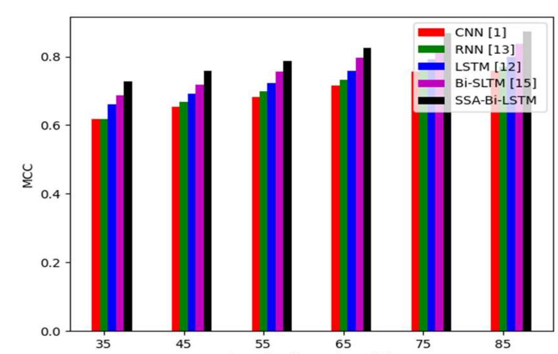

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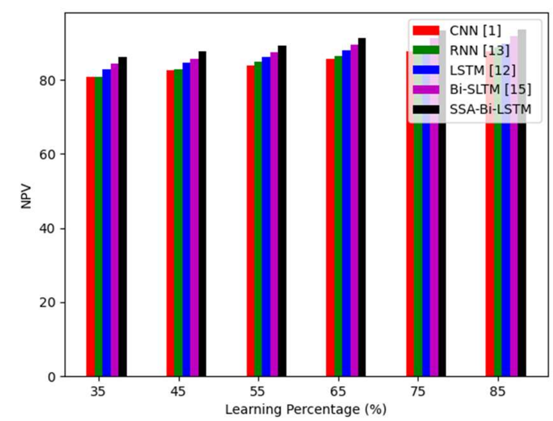

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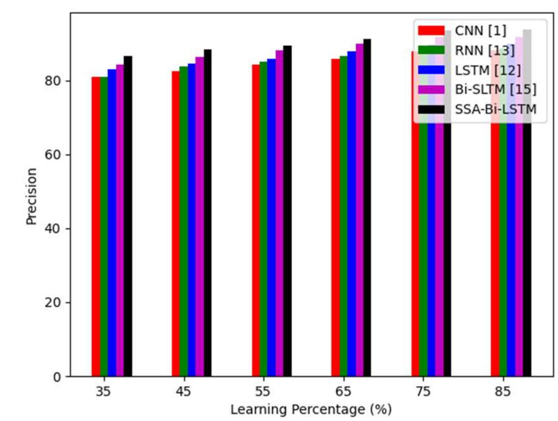

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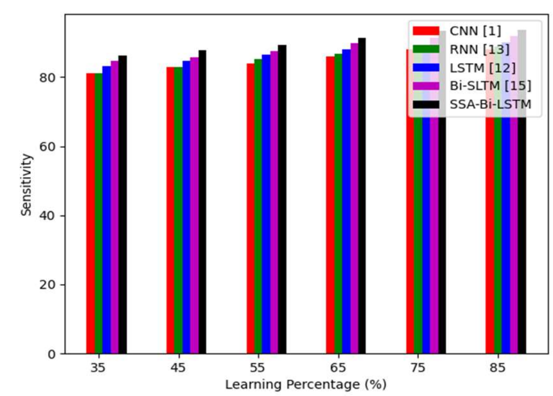

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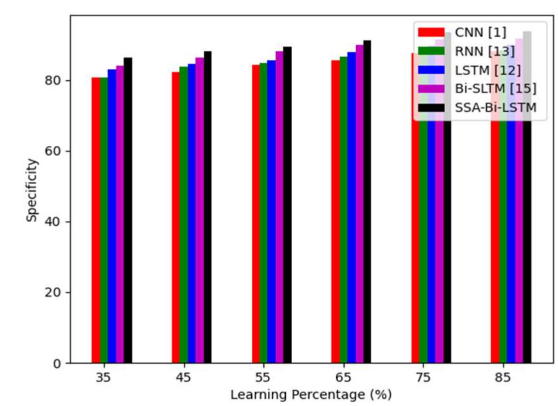

(j)

Fig. 3. Evaluation on proposed arrhythmia classification model with different classifiers in terms of "(a) accuracy, (b) F1-Score, (c) FDR, (d) FNR, (e) FPR, (f) MCC, (g) NPV, (h) precision, (i) sensitivity and (j) specificity"

6.5. Comparative Analysis

The analysis onproposed arrhythmia identification model is estimated by comparing with the different existing techniques as depicted in Table II. The proposed SSA-Bi-LSTM is 19.15%, 10.44%, 12.07% and 18.91% superior to the GWO-Bi-LSTM, HHO-Bi-LSTM, JA-Bi-LSTM and WOA-Bi-LSTM, respectively when the observing the performance of precision. Therefore, the proposed arrhythmia classification model using developed SSA-Bi-LSTM is improved than the existing methods.

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Table II : Overall Performance Of Suggested Arrhythmia Classification Model With Different Algorithms

Algorithm Comparison					
Measures	**GWO-Bi-LSTM [20]**	**HHO-Bi-LSTM [21]**	**JA-Bi-LSTM [22]**	**WOA-Bi-LSTM [23]**	**SSA-Bi-LSTM**
"Accuracy"	0.882044	0.87453	0.896319	0.912847	0.934636
"Sensitivity"	0.879285	0.871833	0.897168	0.913562	0.934426
"Specificity"	0.884848	0.877273	0.895455	0.912121	0.934848
"Precision"	0.885886	0.878378	0.897168	0.913562	0.935821
"FPR"	0.115152	0.122727	0.104545	0.087879	0.065152
"FNR"	0.120715	0.128167	0.102832	0.086438	0.065574
"NPV"	0.878195	0.870677	0.895455	0.912121	0.933434
"FDR"	0.114114	0.121622	0.102832	0.086438	0.064179
"F1-Score"	0.882573	0.875093	0.897168	0.913562	0.935123
"MCC"	0.764107	0.74908	0.792623	0.825683	0.869265
Classifier Comparison					
Measures	**CNN [11]**	**RNN [8]**	**LSTM [7]**	**Bi-SLTM [10]**	**SSA-Bi-LSTM**
"Accuracy"	0.877536	0.881292	0.895567	0.91435	0.934636
"Sensitivity"	0.879285	0.879285	0.894188	0.913562	0.934426
"Specificity"	0.875758	0.883333	0.89697	0.915152	0.934848
"Precision"	0.877976	0.884558	0.898204	0.916293	0.935821
"FPR"	0.124242	0.116667	0.10303	0.084848	0.065152
"FNR"	0.120715	0.120715	0.105812	0.086438	0.065574
"NPV"	0.877086	0.878012	0.892911	0.912387	0.933434
"FDR"	0.122024	0.115442	0.101796	0.083707	0.064179
"F1-Score"	0.87863	0.881913	0.896191	0.914925	0.935123
"MCC"	0.755052	0.762594	0.791136	0.828697	0.869265

7. CONCLUSION

This research work has presented a new arrhythmia classification using the developed SSA-Bi-LSTM for effectively classifying the arrhythmia to detect the cardiovascular disease. Initially, the ECG signals were collected and pre-processed for performing the effective feature extraction. The extracted features were given into the optimal feature selection process for acquiring the significant features using the suggested SSA. The classification was done through the optimized Bi-LSTM for classifying the optimal feature, where the parameter optimization was taken place using the suggested SSA.

Through the analysis on the suggested model, it was acquired that the proposed classification model has secured 12.5%, 5.34%, 7.5%, and 7.12% than the "CNN, RNN, LSTM and Bi-LSTM", respectively. Thus, it has been proved the high efficiency of the proposed arrhythmia classification model with ECG signals when compared with the existing techniques.

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