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ENHANCED ARRHYTHMIA CLASSIFICATION SYSTEM FROM ECG SIGNALS VIA HYBRID OPTIMIZATION-BASED IMPROVED 3DCNN-RESNET

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Abstract
Arrhythmia is characterized by aberrant electrical activity of the heart, which can be identified the changes in the Electrocardiogram (ECG). Automatic ECG detection is needed because it is mainly used for detecting arrhythmias. Although several algorithms are implemented for the automatic classification of cardiac arrhythmias based on the characteristics of the ECG, their stratification rate is very less because of the unreliable features of signal characteristics or limited generalization capability of the classifier and it is still difficult to diagnose the arrhythmia disease automatically. At this work, they propose a new hybrid deep learning technique for the classification of arrhythmia from the ECG signal. Initially, the wanted ECG signal is collected from the standard websites and then it is assigned to the preprocessing technique. The preprocessing techniques includes the artifacts removal and peak detection techniques noise removal for the elimination of the unwanted distortions and the noise present in the signal then the resultant signal is fed to the Short-time Fourier transform (STFT) to achieve the spectrogram signals and then the spectrogram signal. Thus, the resultant spectrogram signal is given to the hybrid deep learning architecture that includes the 3DCNN-ResNet for diagnosing the arrhythmia disease. Here, the parameter optimizations take place using the hybrid Artificial Showering Dolphin Swarm Optimization (ASDSO) to increase the classification performance. It classifies the signal into five prominent classes that is Premature Ventricular Contraction (V), Right Bundle Branch Block (RBBB or R), Normal Sinus Rhythm (N), Left Bundle Branch Block (LBBB or L), and Atrial Premature Beat (A). The success of the proposed model is validated through diverse benchmark datasets with the performance validation like recall, precision, accuracy, f-measure and some negative measures.

***Keywords*: Arrhythmia Classification; Electrocardiogram Signal; Short-time Fourier Transform; 3D-Convolutional Neural Network and Residual Neural Network; Artificial Showering Dolphin Swarm Optimization**

1. Introduction

Arrhythmia is a heart disease that caused due to the abnormal function of heartbeats that is the stratification rate of heart beat is too slow known as bradycardia and the heart beat may be too high it is known as tachycardia. The most common disease that affects all over the people in the world is cardiac disorder [9]. On the basis of records produced by World Health Organization (WHO), it is said that this cardiac disorder causes 30% of death rates all over the world [10]. The death rates get increases due to cardiac disorder, mainly this Cardiac arrhythmia causes greater mortality rates and it causes the heart to function unsystematically. Moreover, it causes changes in the heart beat rates [11]. This disease causes the heart to function abnormally making the heart to beat too slow or making heart to beat too fast and thereby, changing the entire heart beat rate and not supplying sufficient amount of blood supply to other human body parts. As this causes the abnormalities in the blood flow and the main human body part brain does not gets enough amount of blood supply from heart to function regularly and finally this increases the mortality rates [12]. It is more important to monitor this disease regularly and this causes more damages to human body parts. It is also a prime function to detect this disease at earlier stage and should be given treatment to make the heart function normally by supplying sufficient amount of blood to other body parts. It is said that the cardiac arrhythmia disorder is of two types among that one is curable, and there is a possibility for the heart beats are made to function regularly by proper medical treatment and other is non-curable which causes high mortality rates all over the world [13].

ECG is one of the top most apparatus used for predicting and recognizing this cardiac arrhythmia disorder. This equipment records the electrical signals from heart and identifies the cardiac disorder. The electric signals which cause the heart to beat are collected from the human bodies by the electrodes and that are placed on the chest of human bodies. In order to improve the treatment and diagnosis of cardiac arrhythmia many computer based identification and confirmation system has been evolved to predict the heat beat function and classify the heart beat rhythm. These computer vision-based technologies have been adapted as the conventional health centers fails to predict the cardiac arrhythmia at earlier stage [14]. Then, the help of conventional machine learning approaches, the function of heart beat was classified by researches [15]. The function of heart beat was monitored by a device known as ECG. This device is less expensive and this determines the fatty substances, blockages and other criteria present in the heart and thereby, causing the abnormalities in the function of the heart beat [16]. The major physical activity of heart beat is indicated in the form of electric signals with the help of ECG. The ECG record of heart in a particular patient is obtained by placing the electrodes, which is connected to the human body. These electrodes from the ECG apparatus are connected to the chest of the human body and thereby, producing an electric signals generated by human heart [17]. Three types of waves are generated when electrodes are connected to human body. The waves which are generated are QRS complex waves, and T waves. There are four stages of classification of heart beat function; the first phase involves the pre-processing of collected electrical signals from human body. The second stage is segmentation of heart beat rhythm [18]. The third phase of ECG is feature extraction and the final phase is differentiating the classifiers [19]. The removal of noises from the collected signals is carried out by the data pre-processor.

The existing conventional techniques which are used for the detection and diagnosis of cardiac arrhythmia shows a greater drawback in detecting the disease in earlier stage and thereby, leading a challenges to extract the feature which are used for predicting the disease. As the extraction of features from selected aspects becomes difficult in conventional techniques it requires more time for evaluating the data and it is very difficult to analyze. Though the extraction of features is difficult there is a chance of producing a result with low accuracy and precision during the prediction of cardiac arrhythmia in earlier stage. In order to overcome this defect, a well defined ECG apparatus has been developed which the feature extraction processes. This apparatus consumes less amount of time for computing and evaluating the heart beat function [20]. The ECG apparatus extracts the feature from complex electrical signals and it converts that complex feature into a simple feature and thereby, producing a result with higher accuracy and precision in detecting the cardiac arrhythmia disorder in earlier stage [21]. The Deep Belief Networks (DBN) models and Restricted Boltzmann machines (RBM) from deep learning are used for categorization of collected signals [22]. There is different deep learning approaches have been used for extracting the features from selected aspects. Among various techniques of deep learning DBN is widely used as this extracts the features even from a noisy and disturbed signals [23]. Another most commonly used deep learning technique is Convolutional Neural Networks (CNN), which have hierarchical deep layers and has an ability of extracting hierarchies of features. This CNN extracts the signals from noisy signals and it clearly differentiates the various classification functions of heart beat. The presence of hierarchical deep layers, the CNN can extract the data from selected aspects [24]. Res-Net and VGG-nets are the two well defined pre-trained CNN, but these pre-trained CNN cannot be used for the extraction of features from selected aspects. It does not have the ability to use a one dimensional image and this fails to produce result with high accuracy. These pre-trained CNN's does not extract the features from noisy signals and thereby, it consumes more time for computation of signals to produce efficient results. Various researches shows that a morphological feature has been adapted for the extraction of features and hence, it produces better images of heart beat function [25]. In order to produce a perfect image of heart beat function an image tool is required. The Deep Learning technique CNN computes and defines the each classification of image with high accuracy and it shows greater performance for defining the image used for earlier prediction of cardiac arrhythmia disorder. Below descriptions are contributions of the recently suggested deep learning-based arrhythmia classification system.

- To design a powerful deep learning related disease diagnostic model for the classification of arrhythmia disease that would collect a range of patient data in real time and help to identify the heart electrical signals to avoid the risk of the patient.

- To demonstrate an effective hybrid optimization algorithm ASDSO for optimizing the parameters in the developed classifier. The implemented ASDSO efficiently optimizes the epochs and activation function in the ResNet and also the epochs, activation function, and batch size in the 3DCNN to increase the effectiveness of the developed arrhythmia disease classification system in terms of improved accuracy.
- To design the 3DCNN-ResNet-based classification framework with parameter optimization to classify the arrhythmia disease very efficiently at early stage.
- To verify the effectiveness of the implemented system by comparing the performance of developed model over different arrhythmia disease detection techniques and various heuristic algorithms in terms of several validation measures.

Remaining sections are used to structure the deep learning-based arrhythmia classification system are given as below. The procedures to be used for diagnosing various diseases, together with their characteristics and difficulties, are illustrated in II part. Part III provides information on the dataset used to develop the disease diagnostic model, the collecting of signals, and the architectural description of the model. Part IV explains the details for the hybrid heuristic algorithms used to optimize the features from the acquired signals. The constructed 3D-CNN-ResNet model for the categorization of heart disease details is described in part V. The conclusion of the recommended deep learning related disease diagnostic model is described in part 7.

2. Literature survey

2.1. *Related Works*

In 2019, Ram and Kumar [1] have proposed a deep learning technique based on CNN for detecting the arrhythmia heart disease . This CNN deep learning technique has been evolved with 11 layers of convolution. The publically available dataset, which gives standard investigation material for the identification of heart arrhythmia, is MIT-BIH arrhythmia database. By the usage of SMOTE technique, the difference between minority classes and other imbalances that occur in various networks were classified. On the basis of American National Standards Institute (ANSI)–AAMI standards, CNN were classified into five different classes. Here, CNN was completely modified to classify different classes and also to extract the features from selected aspects. The main objective of this advanced CNN technique was to detect the arrhythmia with reduced time consumption for analyzing the signals. By the usage of modified CNN, it could be accepted the exact signal from noisy and disturbed signals. The complex waves such as QRS waves were also detected into a simple wave for easy classification. The improved CNN structure was trained in augmented ECG database. The experimental outcome showed that it given greater accuracy and precision while detecting the cardiac arrhythmia at earlier stage when compared with other conventional deep learning techniques.

In 2019, Chen *et al.* [2] have proposed a new ideology for detecting the classification of ECG signals. An improved Two-Dimensional (2D) CNN deep learning technique has been evolved to detect the disease in earlier stage. Mainly, five types of heart beat function were taken in to account. The five heart beat types were Atrial Premature Right Bundle Branch Block Beat (RBB), Normal Beat (NOR), Contraction Beat (APC), Left Bundle Branch Block Beat (LBB) and Premature Ventricular Contraction Beat (PVC). The proposed 2D-CNN structure obtained the ECG signal from MIT-BIH arrhythmia dataset. The collected signals were optimally selected from the extracted features of noisy signals. The conventional technologies based on One Dimensional (1D) CNN structure do not extract the features from collected signals. Hence, this advanced 2D-CNN was adopted. This 2D-CNN classified the five different heart beat function and it performed optimal classification to differentiate various classification of ECG signals. This proposed model was compared with conventional technologies and the experimental outcome performed greater accuracy in classifying the ECG signals for predicting the disease at earlier phase.

In 2019, He *et al.* [3] have proposed advanced deep learning technique based on Deep Neural Networks (DNN's). Here, Bidirectional and residual convolutional modules were combined and the features were extracted from the collected signals. China Physiological Signal Challenge (CPSC) algorithm has been adopted in this technique. Thus, the result was given high F1 score and scalability. When compared with other existing techniques, this given a higher accuracy for detecting the disease in earlier stage.

In 2020, Tanaji *et al.* [4] have introduced a newly advanced deep learning technique known as General Sparsed Neural Network (GSNN). GSNN was adopted to extract signals from ECG and the collected signals were fed into pre-processor for detecting arrhythmia. MIT-BIH dataset have been adapted for feature extraction process from collected signals. MATLAB software has been adopted to evaluate the results. The different phases of ECG signals were adopted from MIT-BIH dataset. The extraction of signals from noisy circumstances was done with GSNN. Thus the proposed GSNN model showed greater performance for predicting the cardiac disorder. The major objective of the proposed model was to propose an effective neural network. In comparison, with the traditional technologies, this had shown improved scalability, greater accuracy and precision while detecting the disease.

In 2020, Khatibi and Nooshin *et al.* [5] have demonstrated a K-NN technique for detecting the cardiac disorder. This proposed method classified four different types of heart beat function. The feature extraction was done by K-NN technique and the extracted features were further classified on the basis of different classifiers. The classifier that was used for the processing of extracted features was decision trees, random forest, Support Vector Machine (SVM) and K-NN with various kernels. The major objective of this proposed research paper showed that the computation time of signals were very low when compared with other traditional technologies. The feature extraction also consumed a less amount of time. The experimental result showed that it given high specificity and sensitivity rate and also the outcome shown that the accuracy rate was high in detecting the cardiac disorder.

In 2022, Kuncan *et al.* [6] have proposed arrhythmia classification using ECG signals with the usage of a deep learning technique LSTM. LSTM and Angle Transform (AT) method were combined together in order to classify the patterns in ECG. The modified AT method used angular data from neighboring signals to describe the classification from ECG signals. Histograms were used to determine the new signals produced in ECG and also to differentiate three phases such as Normal Sinus Rhythm (NSR), CHF and ARR. This modified LSTM and AT methods easily classified various signals in ECG. To improve the scalability and effectiveness of the proposed model, the distant of the signals was increased.

In 2016, Subasi and Alickovic [7] have proposed a advanced deep learning technique known as Random Forests (RF) classifier for the classification of different ECG signals. The extraction of features from selected aspects was done using this advanced RF classifier. The decomposition of ECG signals was done by Discrete Wavelet Transform (DWT) and the frequency band obtained from DWT indicated the discrimination of wave coefficients. With the usage of DWT, various cardiac arrhythmias were detected at earlier stage. This DWT possessed 10 fold cross validation of deep layers for the differentiation of various classifiers using ECG signals, which detected the cardiac disorder at earlier phase. The experimental results showed that the advanced DWT predicted the disease at earlier stage while compared with other traditional deep learning techniques.

In 2020, Subudhi *et al.* [8] have proposed an advanced multi domain feature extraction that was derived from ECG signals. The proposed method automatically detected the various classifications of ECG signals with the help of C4.5 decision tree classifier. MIT-BIH Arrhythmia Database was recommended for feature extraction of patterns from ECG. A recently developed deep learning technique known as SVM has been adopted for the automatic detection of ECG electrical signals. In total, it comprised of 15 features among that four features were taken and given to Variation Mode Decomposition (VMD), RR intervals, and eight features from Empirical Mode Decomposition (EMD). The proposed classifier namely C4.5 decision tree classifier obtained better results in classification of cardiac arrhythmia. The computation time was low and hence, the error occurrence was also reduced.

2.2. *Problem statement*

The detection of arrhythmia disease using the ECG signal is very difficult because there is a minute variation in the ECG signal. The false prediction and the late prediction of this disease may leads to several problems for the peoples. Hence, the early detection of arrhythmia disease prevents the people from the severe impacts. The features and the challenges of the deep learning-based approaches were listed in the Table 1.

Author [citation]	**Methodology**	**Advantages**	**Disadvantages**
Ram and Kumar [1]	CNN	• It has the possibility of continuous intermediate-term monitoring. • It is more convenient and the affordable disease detection approach.	• It has acquired with high proportion of false alerts for the ECG confirmation. • The total computation time of the detection process is high.
Chen et al. [2]	1D-CNN	• It has the ability to reduce the latency and increase the throughput. • Computation complexity of the system is highly reduced.	• The training time required for the classifier is high. • It has low generalization capability.
He et al. [3]	DCNN	• It gives early warning about the disease at the initial stage. • It reduces the cardiologist's workload.	• It does not give the conclusive guidelines about the diagnosis of the arrhythmia from the ECG signal. • It does not detect the disease accurately.
Tanaji et al. [4]	GSNN	• The recognition rate is high. • It requires limited number of parameters for the entire prediction.	• It is highly sensitive to different type of noises. • It creates a high gap between the deep features and the dataset size.

Khatibi and Nooshin et al. [5]	K-NN	• It accomplished with low loss and high accuracy. • It is highly suitable in the detection of arrhythmia disease with high dimensional data.	• It has provided with high rate of false alarms in the monitoring process. • It has poor sensitivity and specificity.
Kuncan et al. [6]	LSTM	• It provides high precision, recall and f1-measure. • It reduces the root mean square error and mean square error.	• It does not meet the morality and the morbidity requirements. • It is non-invasive in nature.
Subasi and Alickovic et al. [7]	RF	• It provides higher interoperatability. • It leverages the large number of episodes.	• Several improvements are required for increasing system scalability. • The threshold selection process is difficult.
Subudhi et al. [8]	SVM	• It avoids the underfitting and the overfitting problems. • The effectiveness of the system is high precision, recall, accuracy, and f-measure.	• The reliability of the system is poor. • It does not automatically extract the high level features.

Table 1. Features and challenges of previous arrhythmia classification models with ECG signal

CNN [1] has the possibility of continuous intermediate-term monitoring. Further, it is more convenient and the affordable disease detection approach. Nonetheless, it has acquired with high proportion of false alerts for the ECG confirmation. Thus, the total computation time of the detection process is high. 1D-CNN [2] has the ability to reduce the latency and increase the throughput. In addition, the computation complexity of the system is highly reduced. Consequently, the training time required for the classifier is high and therefore, it has low generalization capability. DCNN [3] gives early warning about the disease at the initial stage. Moreover, it reduces the cardiologist's workload. But, it does not give the conclusive guidelines about the diagnosis of the arrhythmia from the ECG signal. In addition, it creates a high gap between the deep features and the dataset size. GSNN [4] gives early warning about the disease at the initial stage and hence it reduces the cardiologist's workload. Yet, it is highly sensitive to different type of noises. Further, it creates a high gap between the deep features and the dataset size. K-NN [5] accomplished with low loss and high accuracy and therefore it is highly suitable in the detection of arrhythmia disease with high dimensional data. In addition, it has provided with high rate of false alarms in the monitoring process. Nevertheless, it has poor sensitivity and specificity. LSTM [6] provides high precision, recall and f1-measure. Furthermore, it reduces the root mean square error and mean square error. Even though, it does not meet the morality and the morbidity requirements and also it is non-invasive in nature. RF [7] provides higher interoperatability. Moreover, it leverages the large number of episodes. Several improvements are required for increasing system scalability. Yet, the threshold selection process is difficult. SVM [8] avoids the underfitting and the overfitting problems. In addition, the effectiveness of the system is high precision, recall, accuracy, and f-measure. But, the reliability of the system is poor. Moreover, it does not automatically extract the high level features.

3. Arrhythmia classification framework using advanced deep elarning on EEG signal

3.1 EEG Dataset Details

The two ECG signals datasets such as "ECG-ID Database and ECG signals (1000 fragments)" are utilized for this newly developed arrhythmia classification model..

Dataset 1 (ECG-ID Database): The EEG signal dataset is gathered from the link: "https://physionet.org/content/ecgiddb/1.0.0/: access date: 2022-11-10". This ECG dataset contains 310 ECG signal recordings that are specified in 90 individual classes.

Dataset 2 (ECG signals (1000 fragments)): The EEG signal dataset is gathered from the external source link: "https://data.mendeley.com/datasets/7dybx7wyfn/3: access date: 2022-11-10". This dataset includes the ECG recordings of 45 patients from 17 classes. The pacemaker rhythm, normal sinus rhythm, and 15 types of ECG signals are presented in this dataset. The ECG signals variations are 360Hz.

The input ECG signal is represented by AT_n^{NI} and the term n is set to be $n = 1,2,...,N$. The total numbers of input signal are indicated by N.

3.2 Architecture of Arrhythmia Classification

Arrthymia heart disease arises due to the irregular heart beat function. When the heart rhythm electrical signal does not work properly then the heart failure, stroke and sudden death is occurred. This leads to increase the mortality rate of the patients. The previous arrhythmia classification model providing better performance but, it contains some drawbacks that are summarized as follows: The given data is not capable of creating a diagnosis of atrial fibrillation. The computational cost required for the implementation is high. To overcome these issues, researches were developed an arrhythmia disease classification model using deep learning techniques and it shows great performance, giving the better results and provide improved solutions in the medical field. These techniques are helpful for researchers in the form of early detection, very safe, integration of devices and keeping appropriate medical records related to diseases. Additionally, the deep learning technique has the potential to reduce the risk of surgery. It offers accurate and exact findings in the medical disciplines. To give greater results over arrhythmia classification an efficient deep structure related framework is developed and the architectural representation of the developed model is given in below Fig. 1.

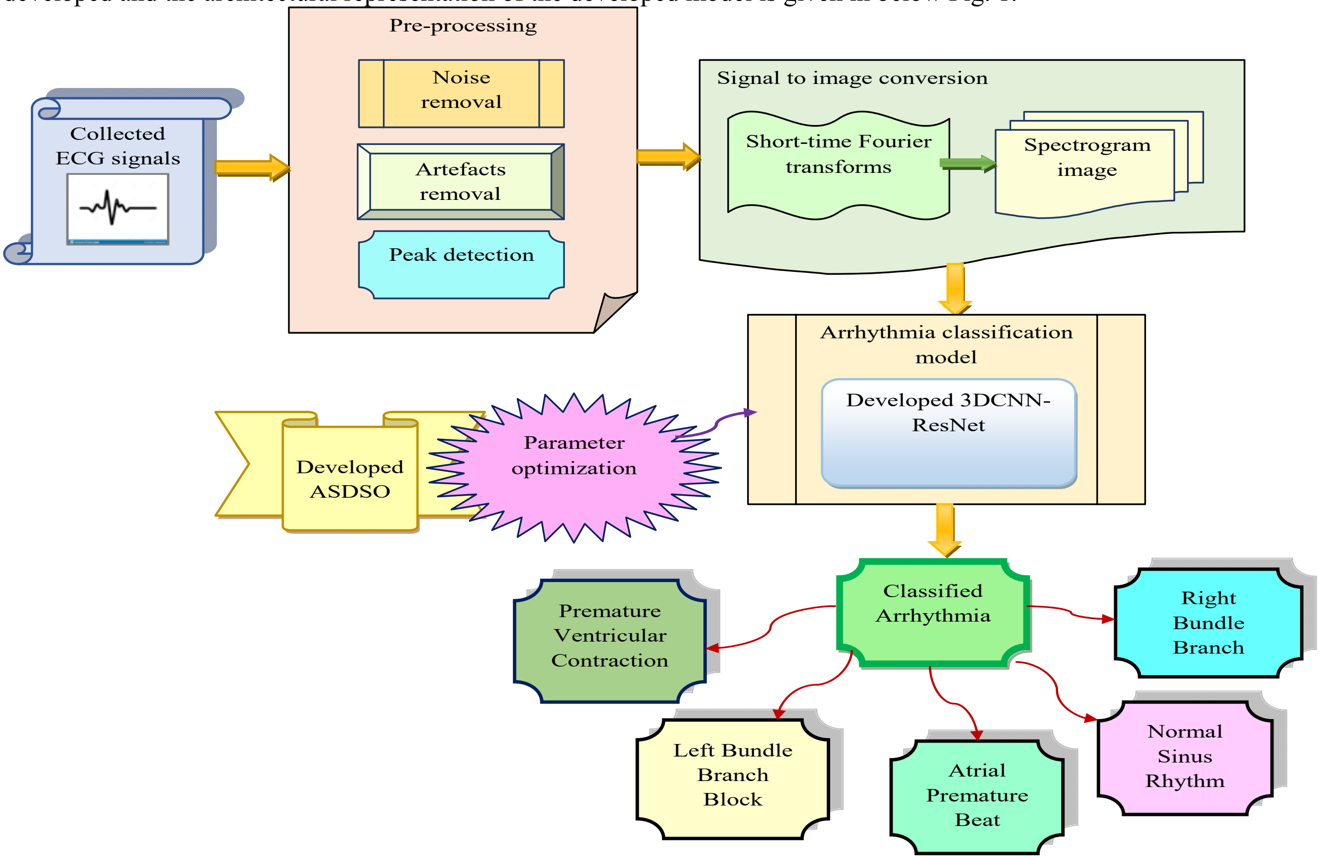


Fig. 1. Structural representation of the designed deep learning-based arrhythmia classification system

The newly developed deep learning-based arrhythmia disease identification system with hybrid optimization is used to classify the arrhythmia disease using the ECG signals. To remove unnecessary missing data from the gathered data by using preprocessing techniques such as noise removal, peak detection, and Artifacts removal. The STFT method is used to extract the spectrogram images from the pre-processed ECG signal. Finally, the obtained spectrogram image is subjected to the classification phase, where the combination of 3DCNN-ResNet methods is used to exactly classify the arrhythmia disease. To increase the effectiveness of the classification stage in terms of accuracy, the developed ASDSO is used to optimize the epochs and activation function in the ResNet are optimized that includes ReLU, sigmoid, tanh and linear function. Moreover, the epochs, activation function and batch size in the 3DCNN model are optimized, where the activation function includes ReLU, sigmoid, tanh and linear function. The designed model performance is greatly and efficiency compared with the other arrhythmia detection techniques.

4. EEG signal pre-processing and spectrogram extraction for Arrhythmia classification: development of novel meta-heuristic algorithm

EEG Signal Pre-processing

The classification process performs better when there is less noise and no disruptions. The newly proposed arrhythmia classification uses peak detection, artifacts removal, and noise removal as preprocessing procedures. The arrhythmia classification approach uses the ECG signal as input that is indicated by AT_n^{NI} .

Noise removal [33]: The ECG signal will be subjected to the noise removal procedure is AT_n^{NI} . The noise removal method is used to reduce the noise in the ECG signals. This strategy mainly removing the noises like Electromyo-Graphic (EMG) noise, power line interference, noises-baseline wander noise, and electrode motion noise. It is used to increase the clear view of the of the ECG signal. The output obtained after noise removal process is indicated by the term AT_n^{RN} .

Artifacts removal [34]: The noise removed ECG signal AT_n^{RN} is given to the input of the artefact removal. In this removal method, the unwanted artifacts are removed from the ECG signals. Then the selected ECG signal features are said to be low pass filter signals. This method helps to increase the quality of the ECG signal. The output obtained after artifacts removal process is denoted by the term AT_n^{AK} .

Peak detection techniques [35]: The ECG signal subjected as input to the peak detection technique is AT_n^{AK} . This method is used to get the morphological features like the location peaks and amplitude from the collected ECG signals. The output ECG signals of the peak detection method are denoted by AT_n^{PD} .

STFT-based Spectrogram Extraction

The ECG signal subjected as input to STFT technique [32] is represented by AT_n^{PD} . The STFT-based method is used to extract the spectrogram image from the collected ECG signal. The ECG data is a non-stationary data. In the evaluation of a non-stationary signal are present in a specified time interval. The non-stationary data is rough stationary data. When a digital signal is discretized, a time-frequency spectrogram is provided. It is shown in below Eq. (1).

$$STFT\{y[m]\} = Y(o,x) = \sum_{m=-\infty}^{\infty} y[m]x[m-o]f^{-kxm} \quad (1)$$

Here, the window function is indicated by $x(m)$. The Hanning window is calculated by Eq. (2).

$$x(m) = \begin{cases} 0.5\left[1-\cos\left(\dfrac{2\pi m}{O-1}\right)\right], & 0 \le m \le O-1 \\ 0 & , \quad otherwise \end{cases} \quad (2)$$

The windows dimension is 512. Finally, they changed ECG time domain signals into spectrum images with the coefficients of 256×256 . The finally obtained spectrogram image of the resultant STFT method is denoted by PS_i^{AF} .

Proposed ASDSO Algorithm

The proposed ASDSO is used to optimize the parameters for increasing the accuracy of the developed deep learning-based arrhythmia classification model. The parameters such as epochs, activation function and batch size in the 3DCNN network is optimized and also the epochs, activation function in the ResNet model are optimized with the usage of this ASDSO. The activation functions include ReLU, sigmoid, tanh and linear function for the both ResNet and 3DCNN. Therefore using this hybrid optimization technique, the effectiveness of the proposed disease classification system is greatly increased. The ASO algorithm [26] used in this deep learning-related disease classification system because it is excellent to take into account of quark mass effects very properly for numerical simulations. The DSO algorithm [27] contains some features that are no specific demand on benchmark functions, periodic convergence, local-optimum-free, and first-slow-then-fast convergence. However, these algorithms need a several improvements to boost convergence rates for high-dimensional spaces. So, they develop a combination of ASO and DSO algorithms to increase the classification performance in terms of accuracy. Based on the condition $K \le q$, it executes the algorithm ASO and DSO. If the condition satisfy means the ASO algorithm is fully updated otherwise the DSO algorithm reception phase is updated. Here, the term K is the parameter to be initialized in the ASDSO algorithm and the term q is a probability and it is selected in the interval of $[0,1]$. A newly adopted K in the ASDSO algorithm is given in Eq. (3).

$$K = \frac{\sqrt{PoP}}{FIT} \quad (3)$$

The term FIT represents a fitness function. The number of population is indicated by PoP .

ASA [26]: It gives successive population of solution in the search space using the iterative process. The following ideas of artificial showering phenomena are given below. All search space given to the imaginary field has no value to flow water and the flow of water is given to the lowest position. This optimization contains no interflow, raining and evaporation of the water. The optimized functions details are given below.

Search space of the solution: The search space of a real function is calculated using Eq. (4) and the function is represented by $g : S^m \rightarrow S$.

$$T = \{y : y \in \Phi \subseteq S^m \wedge m_j \le y_j \le v_j\} \quad (4)$$

Here, the subset is indicated by Φ and the Euclidean field is denoted by S^m. Then, the term y is the location of the irrigation field and the search space irrigation field is represented by T. The landscape level of the location is $g(y)$. The mathematical representation of two dimensional problems is given in Eq. (5).

$$\text{Minimize} \quad g(y) = \left. \begin{array}{c} y_1^2 + y_2^2 \\ y_j \in [-10,10] \end{array} \right\} \quad (5)$$

The search space is reduced as $T = \{y : -10 \le y_j \le 10, 1 \le j \le 2\}$. Then, the four initial populations are given below. $y^{(1)} = (2.5,-4)$, $y^{(2)} = (-5.1,-6.091)$, $y^{(3)} = (8.51,4)$, $y^{(4)} = (-1.1,5.091)$.Next, the above four population landscape levels are given below. $i^{(1)} = g(y^{(1)}) = 22.25$, $i^{(2)} = g(y^{(2)}) = 63.11$, $i^{(3)} = g(y^{(3)}) = 88.42$, $i^{(4)} = g(y^{(4)}) = 27.128$.

Finding the initial population location: The initial population is denoted by $Q^{(0)}$ that is considered in the location of N at the search space T. The corresponding location of the initial population is calculated using Eq. (6).

$$y^{(Rk)} = \left(y_1^{(Rk)}, y_2^{(Rk)}, y_3^{(Rk)}, ..., y_m^{(Rk)}\right) : 1 \le k \le O \quad (6)$$

$$y_j^{(k)} = M_j + rnd \times (v_j - M_j) : 1 \le j \le m \quad (7)$$

Here, the equal initialization set is represented by $I^{(0)}$ and the objective function of the initial set is determined using Eq. (8).

$$I^{(0)} = \{i^{(1)}, i^{(2)}, i^{(4)}, ..., i^{(O)}\} \quad (8)$$

Optimization process using artificial showering: The term $y^{(c)}$ is the best possible solution. In the optimization process, the minimization the best solution value is one and the maximization the best solution value is -1 and it is given in Eq. (9).

$$Q^{(0)} = \{y^{(1)}, y^{(2)}, y^{(4)}, ..., y^{(N)}\} \quad (9)$$

$$y^{(c)} = \arg\left(\min_{1 \le j \le N} \begin{cases} i^{(j)} \, for \min \\ -i^{(j)} \, for \max \end{cases} \right) \quad (10)$$

Then, the best gun-type sprinklers are presented in every location. The steepest downhill direction is indicated by E and it is given in Eq. (11).

$$E = -\nabla g(y) \quad (11)$$

Here, the target location of the sprinkler is represented by $y^{(k)}$ and the current location of the sprinkler is indicated by $y^{(j)}$. The decent direction is denoted by e_1 and it is shown in Eq. (12).

$$e_1 = \begin{cases} y^{(k)} - y^{(j)} & if \; g_k - g_j < 0 \\ y^{(j)} - y^{(k)} & otherwise \end{cases} \quad (12)$$

Next, the best decent direction is represented by e_2 and it is calculated using Eq. (13).

$$e_2 = y^{(best)} - y^{(j)} \quad (13)$$

The gun-type sprinkler and water unit is using the below governing relations that is given in Eq. (14) and Eq. (15) respectively.

$$y^{(j)new} = y^{(j)} + G_j \times \left(t \otimes e_1 / \|e_1\|\right) \quad (14)$$

$$y^{(j)new} = y^{(j)} + G_j \times s \times e_2 / \|e_2\| \quad (15)$$

In the above functions, the term s is a real number between $(0,1)$ and the Minkowski product is $\otimes$. The projection speed of the sprinkler is denoted by G_j and it is measured using Eq. (16). Then, the iterative process is continued still get the possible value.

$$G_j = \left\| y^{(j)} - y^{(m)} \right\| \quad (16)$$

Re-installation: The nature inspired algorithms is present in the local point.

$$\left\| y^{(j)} - y^{(best)} \right\| < \eta \quad (17)$$

$$U_j^{(current)} - U_j^{(allowed)} \quad (18)$$

The false positive value is utilized the positive integer $U_j^{(allowed)}$ and clustering.

DSA [27]: The dolphin algorithm mainly exhibits a dolphin living habits and biological characteristics. The character of dolphin's actual predatory process can be defined as $DP - [y_1, y_2, ..., y_D]^T$. The term M is a number of dolphins and the term $y_k(k = 1,2,3,..., E)$ is an optimized dimension component.

Initialization: The optimal solution is represented by M and the neighbourhood optimal solution is indicated by O . Both optimal solutions is M_j and O_j contains the corresponding variables $M_j(j = 1,2,..., m)$ and $O_j(j = 1,2,..., m)$ respectively.

Distance: The fitness function is denoted by F . Three different distances are used in this DSA algorithm. The first distance from DP_j to DP_k is denotes as $DPP_{j,k}$ and it is shown in Eq. (19).

$$DPP_{j,k} = \left\| DP_j - DP_k \right\| \quad (19)$$

The second distance from DP_j to M_j represents as $DPM_{j,k}$ and it is given in Eq. (20).

$$DPM_{j,k} = \left\| DP_j - M_j \right\| \quad (20)$$

The third distance from M_j to O_j is named as DMO_j and it is calculated using Eq. (21).

$$DMO_j = \left\| M_j - O_j \right\| \quad (21)$$

In this DSA algorithm contains six phases that are search, reception, termination, initialization, and call phases. In the below section explains the four phases like call phase, predation phase, search phase and reception phase.

Search phase: The dolphin makes some sounds during the searching time with random directions R . That sound can be indicated by $W_j = [w_1, w_2, ..., w_E]^T \ (j = 1,2,..., Q)$. Here, the number of sounds is denoted by Q and the variables with each direction are $(K = 1,2,..., R)$. In a particular time u , the new solution is represented by y_{jku} and it is calculated using Eq. (22).

$$y_{jku} = DP_j + W_k u \quad (22)$$

Then, the fitness value F_{jku} is calculated using this new solution and it is shown in below Eq. (23).

$$F_{jku} = Fitnes(Y_{jku}) \quad (23)$$

$$\begin{aligned} F_{jbc} &= \min_{k=1,2,...,Q,u=1,2,...,U_1} F_{jku} \\ &= \min_{k=1,2,...,Q,u=1,2,...,U_1} Fitnes(Y_{jku}) \end{aligned} \quad (24)$$

Next, the individual optimal solution can be measured using Eq. (25).

$$M_j = Y_{jbc} \quad (25)$$

$$Fitnes(M_j) < Fitnes(O_j) \quad (26)$$

Reception phase: The new time is indicated by UT_{jk} .

The new time and the maximum transactions are calculated using Eq. (27).

$$UT_{jk} = 0 \quad (27)$$

$$Fitnes(O_j) > Fitnes(O_k) \quad (28)$$

Call phase: The tem B is a constant value. The new transmission time is given in Eq. (29) and the new updated time is given in Eq. () respectively.

$$UT_{j,k} > \left\lceil \frac{DPP_{j,k}}{B.speed} \right\rceil \tag{29}$$

$$UT_{j,k} = \left\lceil \frac{DPP_{j,k}}{B.speed} \right\rceil \tag{30}$$

Predation phase: In the predation phase, the dolphin encircling radius is denoted by r_2 and the search radius is represented by r_1 and it is measured using Eq. (31).

$$r_1 = U_1 \times speed \tag{31}$$

The dolphin encircling radius r_2 discussed the three cases. Using current information the following Eq. (32) represents the first case. In the first case, encircling radius r_2 is determined by Eq. (33).

$$DPO_j \le r_1 = U_1 \tag{32}$$

$$r_2 = \left(1 - \frac{2}{f}\right) DPO_j \tag{33}$$

After calculating the first case of encircling radius r_2, the new position is determined using Eq. (34).

$$newDP_j = O_j + \frac{DP_j - O_j}{DPO_j} r_2 \tag{34}$$

Using current information, the following conditions presents the second case and it is shown in Eq. (35) and Eq. (36) respectively.

$$DPO_j > r_1 \tag{35}$$

$$DPO_j > DPOM_j \tag{36}$$

In the second case, the encircling radius r_2 is determined by Eq. (37).

$$r_2 = \left(1 - \frac{\frac{DPO_j}{Fitnes(O_j)} + \frac{DPO_j - DPOM_j}{Fitnes(M_j)}}{f.\ DPO_j \frac{1}{Fitnes(O_j)}} \right) DPO_j,\ f > 2 \tag{37}$$

After calculating the second case of encircling radius r_2, the new position is calculated by Eq. (38).

$$newDP_j = O_j + \frac{Rand}{\|Rand\|} r_2 \tag{38}$$

Using current information the following condition is present in a third case that is shown in Eq. (39).

$$DPO_j < DPOM_j \tag{39}$$

In the third case, encircling radius r_2 is calculated using below Eq. (40).

$$r_2 = \left(1 - \frac{\frac{DPO_j}{Fitnes(O_j)} - \frac{DPOM_j - DPO_j}{Fitnes(M_j)}}{f.\ DPO_j \frac{1}{Fitnes(O_j)}} \right) DPO_j,\ f > 2 \tag{40}$$

After calculating the third case of encircling radius r_2, the new position is measured using Eq. (41).

$$Fitnes(newDP_j) < Fitnes(O_j) \tag{41}$$

Here, the condition is satisfied then the algorithm goes at end process otherwise it does not satisfy means again perform the search phase. The pseudocode of the developed ASDSO is expressed in Algorithm 1. The flowchart representation of the presented ASDSO is given in Fig. 3.

Algorithm 1: Implemented ASDSO *Load the number of populations*

Initialize the number of iterations

Initialize the new parameter K

Load the value P with the adaptive concept in Eq. (3).

Get the fitness function

For $J = 1 to M_{iteran}$

For $Z = 1 to N_{popu}$

If $K \leq q$

Set the ASO algorithm

ASO algorithm is fully updated

Else

Set the DSO algorithm

The reception phase is only updated in Eq. (28)

End if

Update the fitness function

End for

Estimate the new position

Final best solution

End

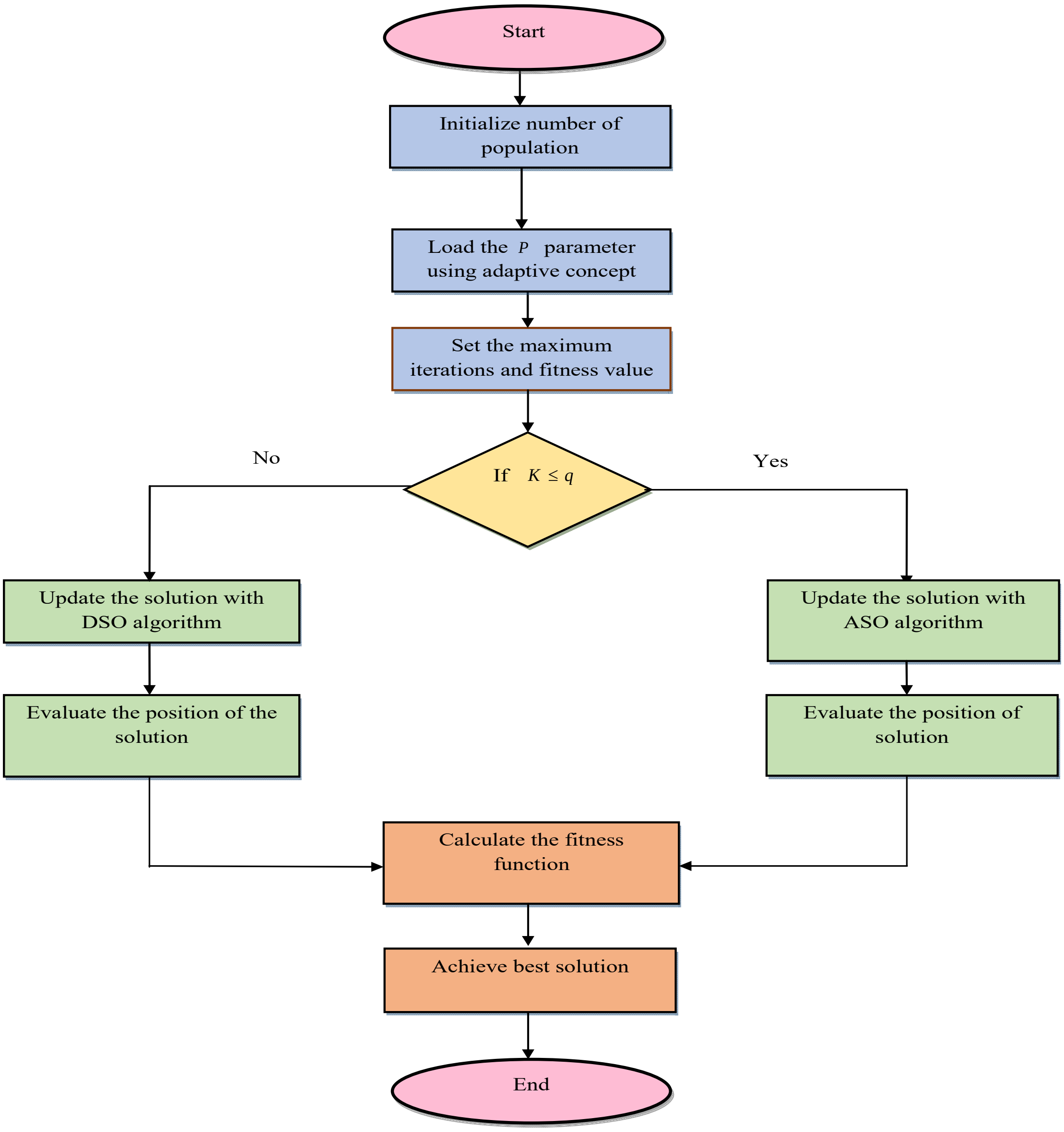


Fig. 2. Flowchart of the implemented ASDSO

5. improvement on EEG signal for Arrhythmia classification

3DCNN Model

The spectrogram image to be forwarded to the 3DCCN-based classification[28] process is PS_i^{AF}. The CNN is a multilayer neural network. The down sample layers and stacking Convolutional layers are adopted to create a 3D Convolutional layer. Next, the feature maps are obtained by the CNN method. The input image is given to the Convolutional layer. Next, the bias term is present in the convolutional layer to activate the function. Then, the Rectified Linear Unit (ReLu) is selected as an activation function. At last, the CNN model contains final output such as feature maps. The voxel positions of the 3D images are considered as a, b and c respectively. The 3D kernel weights are represented by $WE_{lk}^m(\lambda_a,\lambda_b,\lambda_c)$. It connects the m^{th} layer with l^{th} feature maps and k^{th} feature maps to the m^{th} layer, the l^{th} feature maps of the m^{th} layer are termed as G_l^{m-1}. The 3DCNN kernel size of a, b and c is indicated by λ_a, λ_b and λ_c respectively. Then, the 3DCNN kernel filter is indicated by $v_{lk}^m(a,b,c)$. The 3D Convolutional layer is shown in the below Eq. (42).

$$\begin{aligned} v_{lk}^m(r,z,d) &= \sum_{\lambda_a}\sum_{\lambda_b}\sum_{\lambda_c} G_l^{m-1}(a+\lambda_a, b+\lambda_b, c+\lambda_c) \\ &\times WE_{lk}^m(\beta_a,\beta_b,\beta_c) \end{aligned} \tag{42}$$

The next step, adding an activation function of ReLu features that is shown in below Eq. (43).

$$G_k^m(a,b,c) = \max\left(0, C_k^m + \sum_l v_{lk}^m(a,b,c)\right) \tag{43}$$

Here, the bias term is indicated by C_k^m at the m^{th} layer of the l^{th} feature map. Then the result of the summation is denoted by $G_k^m(a,b,c)$ at the l^{th} feature map of various convolution kernels. After the convolutional layer they add the max pooling layer and that max pooling layer contains more compact features.

ResNet Model

The spectrogram image to be forwarded to the ResNet-based classification[36] process is PS_i^{AF}. The resnet method is mainly used to detect the arrhythmia disease. In the resnet method, the target output is indicated by $I(y)$ and the input parameter is denoted by y. The direct residual output $G(y) = I(y) - y$ is determined using the block of the resnet and it creates a target output that is represented by $G(y) + y$. When it contains many convolutional layers the degradation is very faster. The resnet contains so many shortcut connections to avoid the one or two layers and perform the identity mapping indirectly. The residual network reference is indicated by (Y). It is used to optimize the network layers. The resnet contains two layers. The residual mapping function can be determined by Eq. (44).

$$G = A_2\beta(A_1 y) \tag{44}$$

Here, the activation function of ReLu is represented by β. Next, the shortcut connection of second ReLu is represented by z.

$$z = G(y, \{A_j\}) + y \tag{45}$$

Then the term A_t is linear transmission and it is shown in Eq. (46).

$$z = G(y, \{A_j\}) + A_t y \tag{46}$$

Finally, the classified arrhythmia is obtained at the output of the ResNet model.

Optimized 3DCNN-ResNet Model

The spectrogram image is subjected as input to optimized 3DCNN-ResNet model and it is indicated by PS_i^{AF}. The developed deep learning-based 3D-CNN-ResNet arrhythmia classification model is employed to provide very efficient classification results with high accuracy. It is used to reduce the cost and reduce the time complexity. The 3D-CNN framework is primarily used in this deep learning-based arrhythmia classification model because it is simple to develop and easy to train without increasing the error percentage. However, it offers lack of incompatibility with a big number of input data in the diagnosing process. Because optimized 3DCNN-ResNet model efficiently encode hidden patterns and have produced high generalization. In addition, the ResNet networks are the most popular deep learning networks and the capacity is quite poor. Therefore, the deep learning-based arrhythmia classification model with the combination of the 3D-CNN and ResNet network is used to deliver superior diagnosis results. Here, the classification step is independently applied to the chosen features from the input signals. The integrated networks parameters are optimized using the newly developed ASDSO algorithm. Using the newly implemented 3D-CNN-ResNet technique, the epoch and activation function in the ResNet are optimized and the epoch, batch size and activation function in the 3D-CNN are also optimized. The activation functions such as ReLU, sigmoid, tanh and linear function from the both 3D-CNN and ResNet are optimized. The optimized epochs are chosen in the interval of $[50,100]$ and the optimized activation function are chosen in the interval of $[0,3]$ in the ResNet. In addition, the optimized epochs are chosen in the interval of $[50,100]$, the optimized activation function are chosen in the interval of $[0,3]$ and optimized batch size are chosen in the interval of $[10,260]$ in the 3D-CNN. The accuracy of the disease detection procedure might be increased by this ASDSO approach. The objective function OB_F of the designed 3D-CNN-ResNet-based disease diagnostic model measure is calculated using Eq.(47).

$$OB\_F = \underset{\{LR_e^{PE}, PS_i^{AF}, Cp_{ac}^{3DCNN}, Cy_r^{3DCNN}, CD_m^{3DCNN}, RT_k^{Res}, RI_o^{Res}\}}{\arg\min} \left(\frac{1}{A}\right) \tag{47}$$

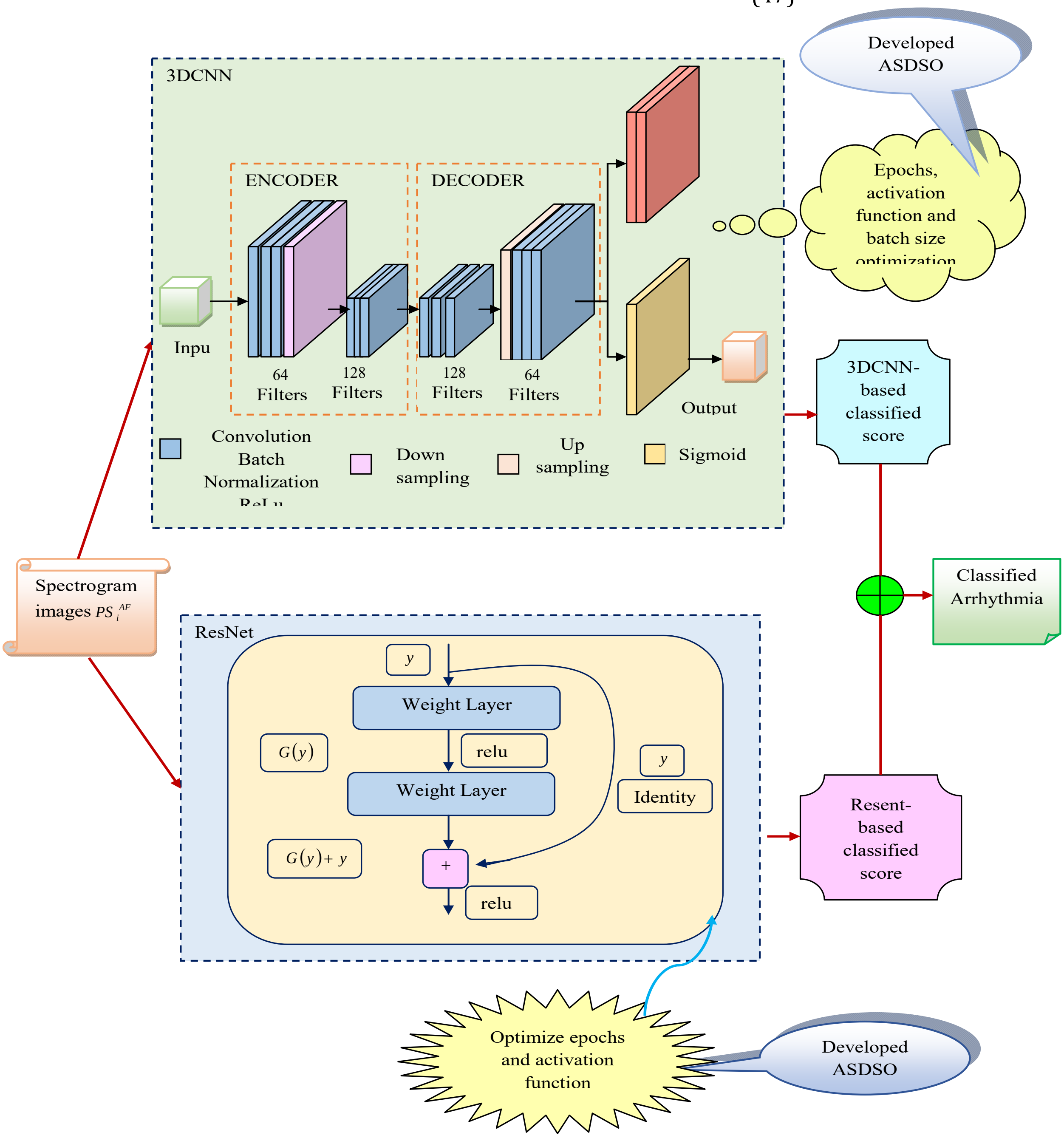


Fig. 3. Optimized 3D-CNN-Res-Net based arrhythmia classification model

The term LR_e^{PE} denotes the preprocessed data, PS_i^{AF} gives the selected features from the spectrogram image features and RT_k^{Res} represents the optimized epochs in the in ResNet and Rl_o^{Res} represents the optimized activation function in the ResNet. The term Cp_{ac}^{3DCNN} denotes the optimized epochs in 3D-CNN, Cy_r^{3DCNN} defines the optimized activation function in 3D-CNN and CD_m^{3DCNN} defines the optimized batch size in 3D-CNN. The term A is the accuracy and it is calculated based on the positive and negative observation values. The accuracy value is determined using below Eq. (48).

$$A = \frac{(KR_a + KR_e)}{(KR_a + KR_e + VR_a + VR_e)} \quad (48)$$

The terms KR_e , KR_a , VR_e and VR_a respectively, denotes the true positive, true negative, as well as the false positive and false negative values. The structural representation of the developed optimized 3D-CNN-ResNet is illustrated in the below Fig. 3.

6. Results and discussions

Experimental setup

Python tool was used in the developed deep learning-related arrhythmia classification technique. With the aid of multiple positive and negative metrics, the performance of the developed 3D-CNN-ResNet-based arrhythmia disease classification model has been verified against other arrhythmia disease classification methodologies. In this designed model, the population size will be set at 10. The actual chromosome length of this model was 5. For these tests, a maximum of 10 iterations were used this developed model. The effectiveness of the developed arrhythmia classification approach was analyzed with the previously utilized detection models and heuristic algorithms to validate the effectiveness. Heuristic algorithms used for these analysis were Single Static Assignment (SSA) [30], Coyote Optimization Algorithm (COA) [31], ASO [27], and DSO [26], while the classification techniques used for this performance analysis was SVM [8], 3DCNN [28], LSTM [6] and 3DCNN-ResNet [29].

Evaluation measures

The implemented technique validation measures are calculated as follows.

(a) Sensitivity: The performance of the developed plant leaf disease detection technique is measured based on the projected true values that are shown in the below Eq. (49).

$$Se = \frac{KR_a}{KR_a + VR_a} \quad (49)$$

(b) Precision: The effectiveness of the developed model is evaluated using precision measures and it is calculated by Eq. (50).

$$Pes = \frac{KR_e}{KR_a + VR_a} \quad (50)$$

(c) Specificity: The specificity is used to calculate true negative samples and it is given in Eq. (51).

$$sp = \frac{KR_e}{KR_e + VR_a} \quad (51)$$

(d) F1-score: The recall and precision averages are used to calculate the F1-score and it is subjected to Eq. (52).

$$F1c = \frac{2 \times KR_a}{2KR_a + KR_e + VR_e} \quad (52)$$

(e) FNR: The FNR determined by calculating the proportion of negative samples to all positive samples and it is measured by Eq. (53).

$$FNR = \frac{VR_e}{KR_e + KR_a} \quad (53)$$

(f) MCC: The MCC value is produced the better results for all confusion matrices and it is shown in Eq. (54)

$$MCC = \frac{KR_a \times KR_e - VR_a \times VR_h}{\sqrt{(KR_a + VR_a)\,(KR_a + VR_e)\,(KR_e + VR_a)(KR_e + VR_e)}} \tag{54}$$

(g) FDR: The FDR value is determined by adding false positive results to all samples, as shown in Eq. (55).

$$FDR = \frac{VR_a}{VR_a + KR_a} \tag{55}$$

(h) FPR: The FPR value is calculated to indicate the proportion of false samples to all negative samples and it is given in Eq. (56).

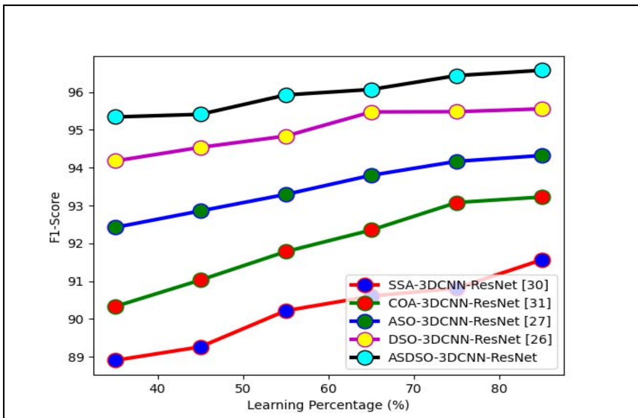
$$FPR = \frac{VR_a}{VR_a + KR_e} \tag{56}$$

(i) NPV: The total number of negative sample is calculated by Eq. (57).

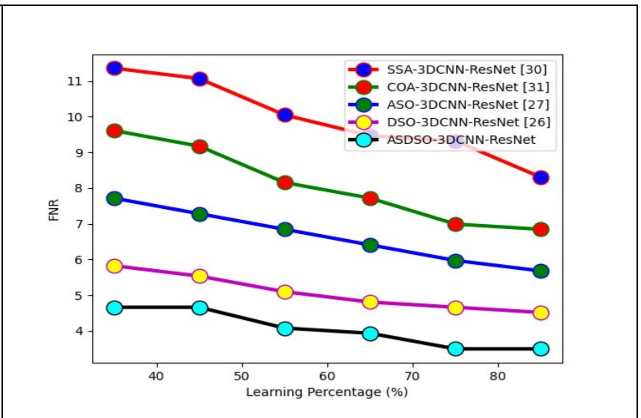
$$Npv = \frac{KR_e}{KR_e + VR_e} \tag{57}$$

Performance evaluation on the implemented arrhythmia classification system over various heuristic algorithms

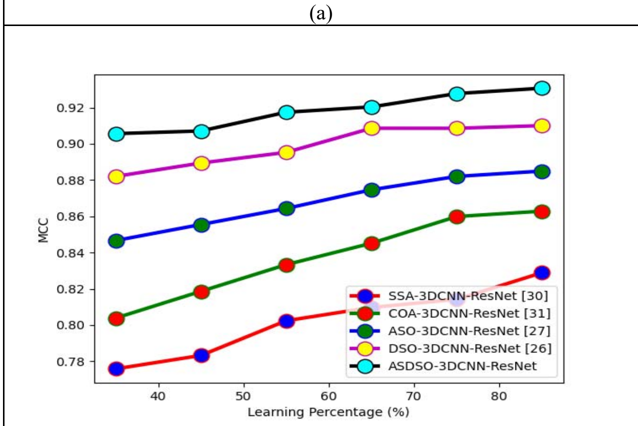
Fig. 4 demonstrates the effectiveness analysis of the newly implemented deep learning-based method for classifying arrhythmia classification model compared with other heuristic algorithms. According to the assessment analysis, the applied ASDSO-3DCNN-ResNet-based arrhythmia classification model has better F1-score of 3.19%, than SSA-3DCNN-ResNet, 4.30% than COA-3DCNN-ResNet, 6.59% than ASO-AC-3DCNN-ResNet and 7.53% than DSO-AC-3DCNN-ResNet with the learning percentage of 55. The proposed ASDSO-3DCNN-ResNet-based arrhythmia classification model outperformed the other algorithms with respect to accuracy.



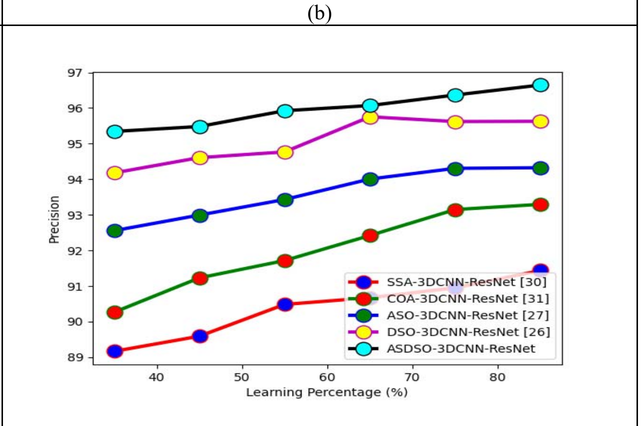
(a)



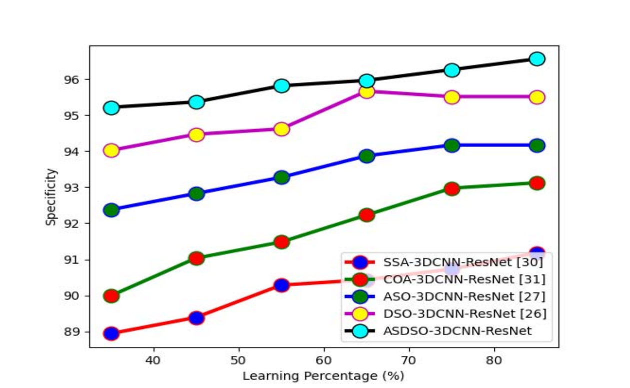
(b)



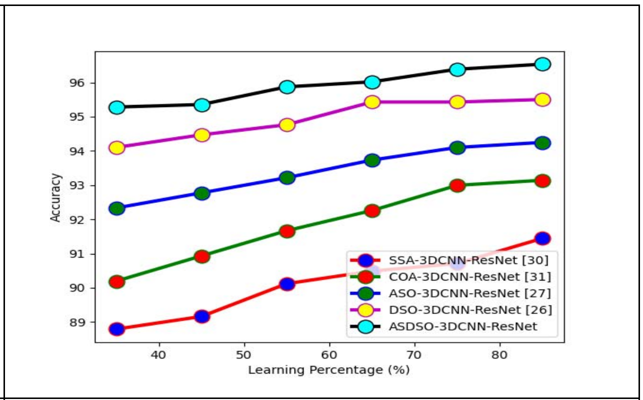
(c)



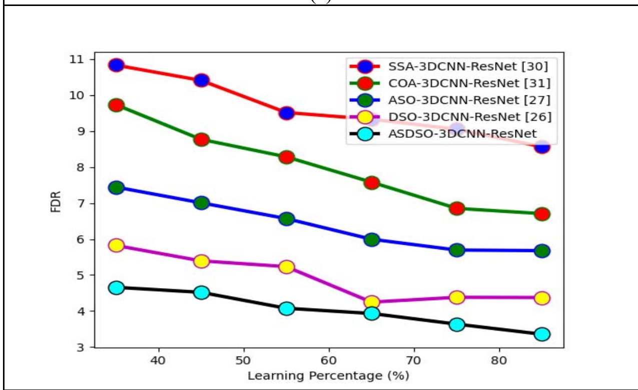
(d)



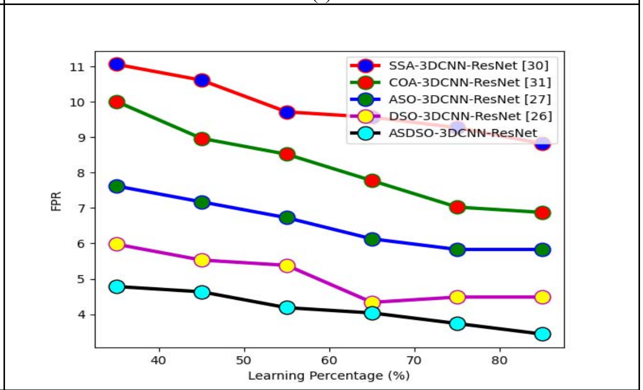
(e)



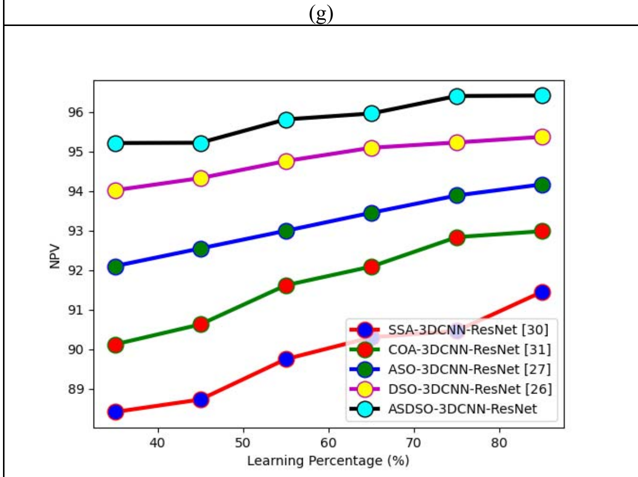
(f)



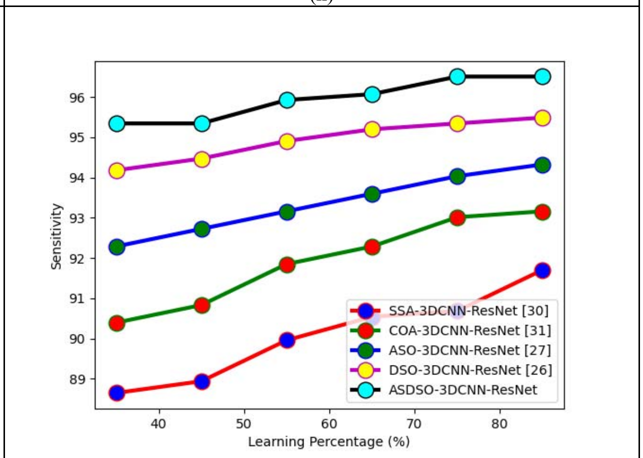
(g)



(h)



(i)

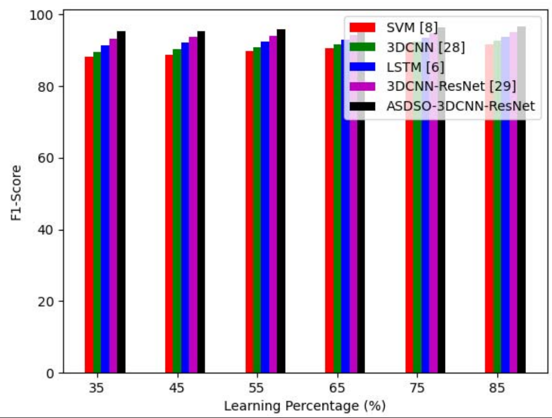


(j)

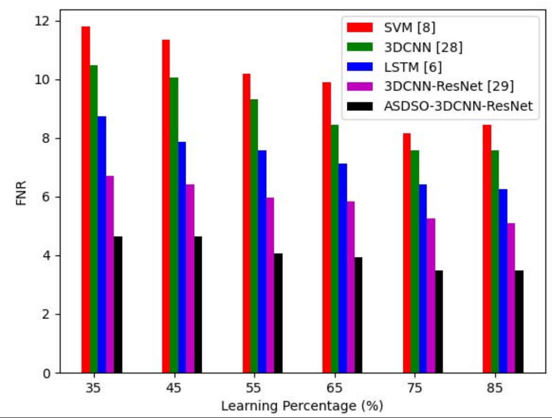
Fig. 4. Efficiency evaluation on implemented deep learning related arrhythmia classification framework over various heuristic algorithms in regards to "(a) F1-Score (b) FNR (c) MCC (d) Precision (e) Specificity (f) Accuracy (g) FDR (h) FPR (i) NPV (j) Sensitivity"

Performance evaluation on the implemented arrhythmia classification system over classification methods

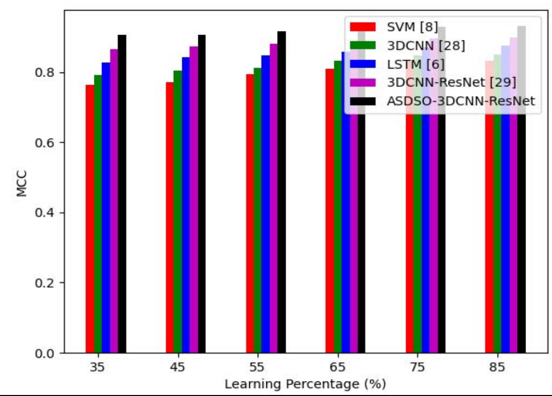
The following Fig. 5 demonstrates the effectiveness of the newly developed deep learning-based method for classifying arrhythmia classification model is compared with other classification techniques. According to the assessment analysis, the applied ASDSO-3DCNN-ResNet-based arrhythmia classification model has increased F1-score of 1.02% than SVM-3DCNN-ResNet, 2.18% than 3DCNN-3DCNN-ResNet,9.21% than LSTM-3DCNN-ResNet, and 9.33% than 3DCNN-ResNet-3DCNN-ResNet with the learning percentage of 55. The proposed arrhythmia classification model outperformed the other approaches in terms of accuracy.


SVM [8]
3DCNN [28]
LSTM [6]
3DCNN-ResNet [29]
ASDSO-3DCNN-ResNet
F1-Score
Learning Percentage (%)

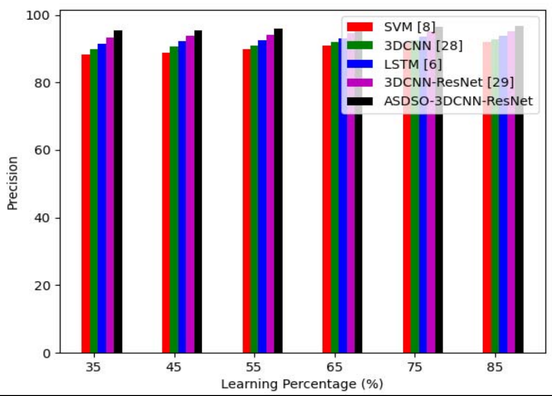
(a)


SVM [8]
3DCNN [28]
LSTM [6]
3DCNN-ResNet [29]
ASDSO-3DCNN-ResNet
FNR
Learning Percentage (%)

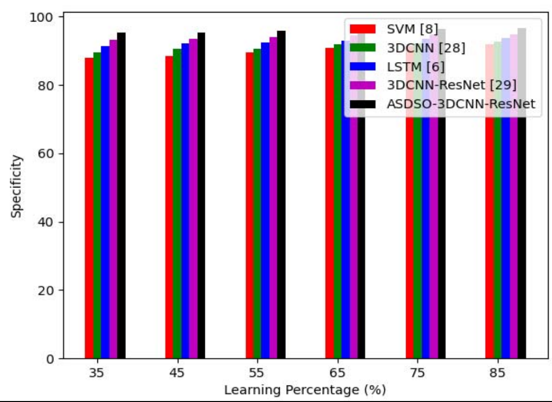
(b)


SVM [8]
3DCNN [28]
LSTM [6]
3DCNN-ResNet [29]
ASDSO-3DCNN-ResNet
MCC
Learning Percentage (%)

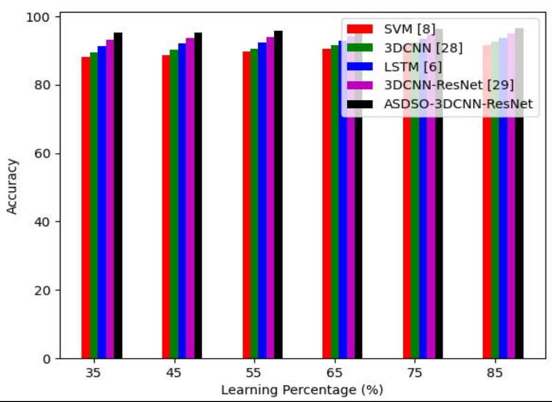
(c)


SVM [8]
3DCNN [28]
LSTM [6]
3DCNN-ResNet [29]
ASDSO-3DCNN-ResNet
Precision
Learning Percentage (%)

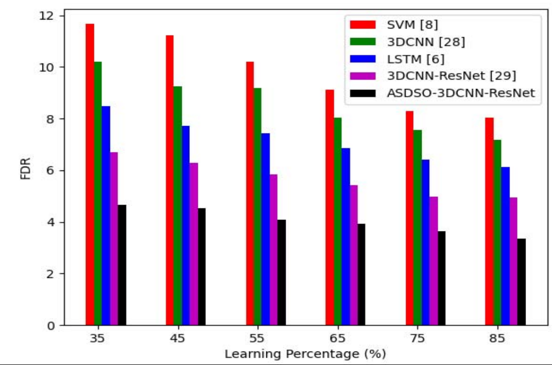
(d)


SVM [8]
3DCNN [28]
LSTM [6]
3DCNN-ResNet [29]
ASDSO-3DCNN-ResNet
Specificity
Learning Percentage (%)

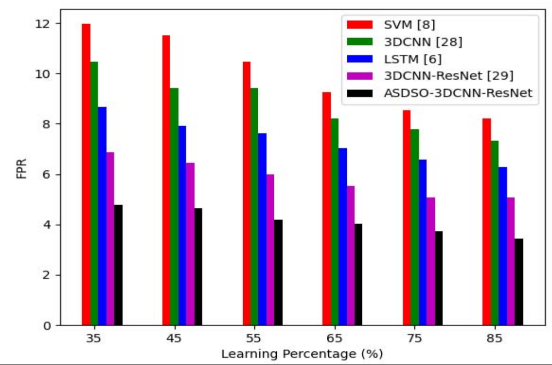
(e)


SVM [8]
3DCNN [28]
LSTM [6]
3DCNN-ResNet [29]
ASDSO-3DCNN-ResNet
Accuracy
Learning Percentage (%)

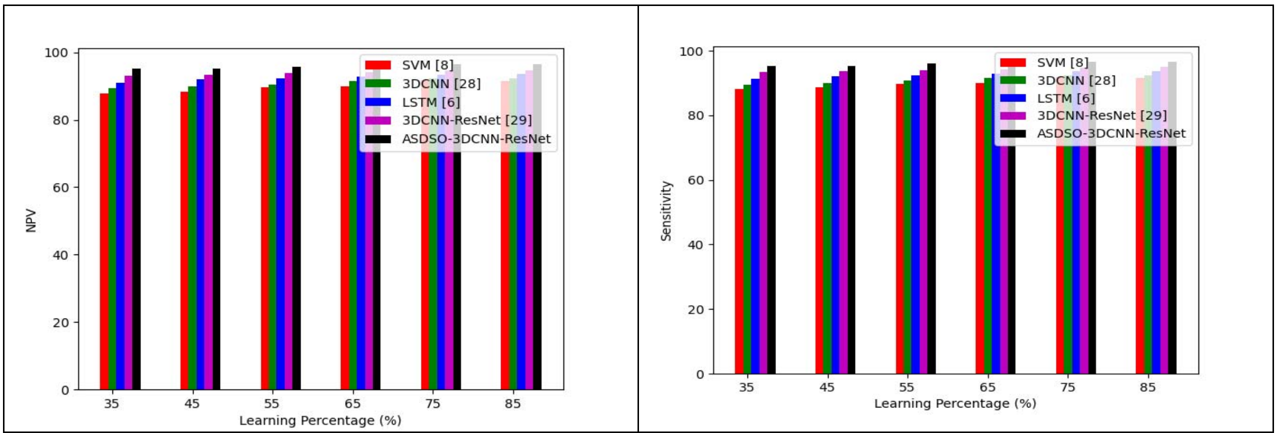
(f)


SVM [8]
3DCNN [28]
LSTM [6]
3DCNN-ResNet [29]
ASDSO-3DCNN-ResNet
FDR
Learning Percentage (%)

(g)


SVM [8]
3DCNN [28]
LSTM [6]
3DCNN-ResNet [29]
ASDSO-3DCNN-ResNet
FPR
Learning Percentage (%)

(h)



(i) (j)

Fig. 5. Efficiency evaluation on implemented deep learning related arrhythmia classification framework over various methods in regards to "(a) F1-Score (b) FNR (c) MCC (d) Precision (e) Specificity (f) Accuracy (g) FDR (h) FPR (i) NPV (j) Sensitivity"

Overall analysis of the developed arrhythmia classification system

Several heuristic algorithms and conventional arrhythmia disease classification techniques are used to validate the newly implemented ASDSO-3DCNN-ResNet-based arrhythmia disease diagnostic model. Table II shows the comparison analysis of various heuristic algorithms on the developed model. Table II compares the performance analysis of the proposed arrhythmia diagnostic model with several existing techniques of arrhythmia disease detection model. The developed arrhythmia classification system shows the better performance in terms of F1-score of 1.0% than SSA-3DCNN-ResNet, 2.40% than COA-3DCNN-ResNet, 3.60% than ASO-AC-3DCNN-ResNet, and 6.18% than DSO-AC-3DCNN-ResNet. Additionally, the developed arrhythmia strategy would perform better than other recently used approaches.

Measures	SSA-3DCNN-ResNet [30]	COA-3DCNN-ResNet[31]	ASO-3DCNN-ResNet[27]	DSO-3DCNN-ResNet[26]	ASDSO-3DCNN-ResNet
MCC	81.4137	85.9861	88.1994	90.8546	92.7715
Accuracy	90.708	92.9941	94.1003	95.4277	96.3864
F1-Score	90.8163	93.0808	94.1691	95.481	96.4364
Sensitivity	90.6841	93.0131	94.032	95.3421	96.5066
FDR	9.0511	6.8513	5.6934	4.3796	3.6337
Specificity	90.7324	92.9746	94.1704	95.5157	96.2631
NPV	90.462	92.8358	93.8897	95.231	96.4072
Precision	90.9489	93.1487	94.3066	95.6204	96.3663
FNR	9.3159	6.9869	5.968	4.6579	3.4934
FPR	9.2676	7.0254	5.8296	4.4843	3.7369

Table 2. Performance validation of implemented arrhythmia disease diagnostic model with different heuristic algorithms

Measures	SVM-3DCNN-ResNet [8]	3DCNN-3DCNN-ResNet [28]	LSTM-3DCNN-ResNet [6]	3DCNN-RESNET-3DCNN-ResNet [29]	ASDSO-3DCNN-ResNet
MCC	83.3302	84.6581	87.0184	89.6745	92.7715
Accuracy	91.6667	92.3304	93.5103	94.8378	96.3864
F1-Score	91.7818	92.4309	93.5953	94.898	96.4364
Sensitivity	91.8486	92.4309	93.5953	94.7598	96.5066
FDR	8.2849	7.5691	6.4047	4.9635	3.6337
FPR	8.5202	7.7728	6.577	5.0822	3.7369
NPV	91.6168	92.2272	93.423	94.6349	96.4072
FNR	8.1514	7.5691	6.4047	5.2402	3.4934
Specificity	91.4798	92.2272	93.423	94.9178	96.2631
Precision	91.7151	92.4309	93.5953	95.0365	96.3663

Table 3. Validation of implemented arrhythmia disease diagnostic model with different arrythmia diagnostic techniques

7. Conclusion

The recently developed arrhythmia -based arrhythmia disease diagnostic model has been proposed to classify the arrhythmia disease at initial stage and reduce the mortality rate. Two different datasets were used to obtain the necessary ECG signal for this newly developed arrhythmia disease detection model. In the initial stage, the pre-processing, techniques such as noise removal, peak detection, and artifacts removal were used. The spectrogram images were obtained from the preprocessed ECG signal using the STFT technique. The final extracted features of spectrogram image were given to the classification section. This section utilized a 3DCNN-

ResNet in order to classify the patterns from the ECG signal. The parameters present in the 3DCNN-ResNet were optimized with the help of developed ASDSO to improve the accuracy rate. The effectiveness of the developed model has been confirmed using a variety of optimization and arrhythmia disease classification strategies, and the test results have demonstrated that the proposed model performed greatly. In comparison to the implemented system, the recommended disease classification model was confirmed with increased F1-score of 1.62% than SVM-3DCNN-ResNet, 3.03% than 3DCNN-3DCNN-ResNet,4.33% than LSTM-3DCNN-ResNet, and 5.07% than 3DCNN-ResNet-3DCNN-ResNet. Moreover, the experiment analysis shown the overall effectiveness of the designed disease classification system was significantly enhanced.

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Conflicts of interest

The authors have no conflicts of interest to declare.

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