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Internet of Things Enabled Based Arrhythmia Classification using Dandelion Optimization Algorithm with Ensemble Learning

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Abstract

Internet of Things (IoT) based Arrhythmia Classification is a cutting-edge algorithm that amalgamates the abilities of the IoT and advanced medical diagnosis to revolutionize the detection and classification of arrhythmias—irregular heartbeats that may indicate fundamental cardiovascular issues. This technique leverages IoT devices, namely connected health monitors and wearable sensors, to continuously gather electrocardiogram (ECG) information from individuals. This information, streamed in real-time, provides a great opportunity for timely and remote monitoring of cardiac health. Leveraging the abilities of deep learning and IoT, this technique provides an automated and more sophisticated means of classifying and detecting arrhythmias, improving the efficiency and accuracy of diagnoses. This article presents an Internet of Things Enabled Based Arrhythmia Classification using the Dandelion Optimization Algorithm with Ensemble Learning (AC-DOAEL) method. The presented AC-DOAEL technique utilizes IoT-based data collection with an ensemble learning-based classification process. For the arrhythmia detection and classification process, the AC-DOAEL technique follows an ensemble learning algorithm such as long short-term memory (LSTM), autoencoder (AE), and bidirectional LSTM (BiLSTM) models. To improve the recognition rate of the ensemble models, the AC-DOAEL technique uses DOA as a hyperparameter optimizer. The simulation outcomes of the AC-DOAEL method are well-studied on benchmark ECG data. The experimental result analysis inferred the greater performance of the AC-DOAEL algorithm with other techniques.

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Keywords: Internet of Things; healthcare; Arrhythmia classification; ECG signals; Artificial intelligence

1. Introduction:

Artificial intelligence (AI) and the Internet of Things (IoTs) are developing domains wherever researchers are emerging technologies and methods for minimizing human involvement. While IoT depends on sensors, data processing methods, and communication technology [1]; classification techniques are employed for identifying a concealed sample in the input data and detecting the types where it belongs. It has the potential to implement this technology in areas like meteorology, agriculture, industry, and the medical field [2]. For example, a medical cyber-physical system (MCPS) is a notion wherever networks, software, and sensors interconnect with physical human signals to improve the efficiency of a patient's treatment [3]. In such a manner, the sensor detects biological signals and transmits them over a network, which is processed by software techniques to extract valuable data and proceed with a decision namely producing an alert, analysis, or even offering treatment to simply enhance the patient's medical help [4]. Because of the great expenses related to hospitalization, options containing assisted living, physical activity monitoring, home care, and telemedicine are defined as major attention. Similarly, home and mobile monitoring of important indications and physical activities permit health that can be remotely accessible at any time [5].

Alternatively, cardiovascular disease (CVD) is the major reason of death with an estimated 32% of every death around the world as per the World Health Organization (WHO) [6]. Cardiac arrhythmia is a category of CVDs, that threatens billions of humans and survives worldwide. IoT devices are designed and utilized in several devices for communicating, monitoring, and improving targets. Additionally, it offers data at the correct time without specialist consultation which can be very efficient in rural areas [7]. Arrhythmia cases are diagnosed by aggregating the signals and calculating them by using analytical tools. The simplest method to detect arrhythmia is to implement a manual analysis on 24 - 72 hours of ECG. Conventionally, in methods like extended-time ECG recordings, patients are required to wear Holter Monitor for a continuous time, which can be a more unpleasant experience [8]. The fast development of IoT approaches has created new methods such as Fitbit, Android Wear, or Apple Watch, for monitoring the conditions of the heart. Conversely, the ubiquity of IoT-based devices has also led to a significant rise in ECG data [9], causing an important challenge to ECG analysis. Manual analyses have been time-saving and error-prone which is no more potential. An automatic technique can be extremely required for providing a low-cost analysis for arrhythmia and permitting at-risk patients to receive early treatments [10].

This article presents an Internet of Things Enabled Based Arrhythmia Classification using the Dandelion Optimization Algorithm with Ensemble Learning (AC-DOAEL) method. For the arrhythmia detection and classification process, the AC-DOAEL technique follows an ensemble learning algorithm such as long short-term memory (LSTM), autoencoder (AE), and bidirectional LSTM (BLSTM) models. To improve the recognition rate of the ensemble models, the AC-DOAEL technique uses DOA as a hyperparameter optimizer. The simulation values of the AC-DOAEL methodology are well-studied on the benchmark ECG database.

2. Related Works

Chen et al. [11] established a VANet architecture for ECG-based application, a small-scale DL-based real-world inference results for VA identification. VANet attains a milli-seconds scale inference rate on diverse architectures. VANet leverages optimizer approaches namely residual links, and framework designs, such as RNNs and transformers, for improving NN effectiveness and reducing storage and computational costs. In [12], an automatic ECG beat classification algorithm depends on the DNN method. This collected data can be analyzed utilizing the DL method, and the outcomes are shared with the chief physician. Abdalla et al. [13] suggested a new approach for automatically classifying 10 various kinds of arrhythmia depending on the DL technique. Therefore, the popular CNN algorithm is modified for classifying various categories of arrhythmia. The framework of this developed method contains eleven layers allocated in this way: a 4-layer as convolution transferred with other 4-layers of max-pooling and the last three are effectively interconnected layers.

In [14], the CAD technique for automatically diagnosing ECG, which comprises adapted DL-NNs to categorize ECG signals into 3 types: normal sinus rhythm, arrhythmia, and congestive heart failure. In this study, the NNs employed such as GoogLeNet and AlexNet. The ECG signals are gathered from virtual sources and later transformed into a scalogram. Thanka et al. [15] introduced an efficient ensemble method with a network-in-network framework that depends on LSTM and CNN for correctly diagnosing arrhythmias in ECG signals. Previously, resampling is established to stabilize the information to prevent the method from the presence of under-fit and over-fit. The ensemble method carried out higher validation data. Hammad et al. [16] focused on offering a lightweight multi-model depending on CNNs, which transferred knowledge from several lightweight DL methods and is transferred into one method to support the detection of arrhythmia through ECG signals. Hence, the method achieved a multi-model ability for classifying arrhythmia from ECG signals.

Bhukya et al. [17] suggested AI techniques for detecting and classifying different cardiac arrhythmia categories employing diverse approaches containing DM, ECG signal analysis, and the NBs method. An NB method to control heart arrhythmias is a supportable tool for medical specialists in detecting and treating the condition. This developed method employed DT-based cardiac arrhythmias for diagnosing and classifying methods. Akhila Naz et al. [18] recommended a dependable and new arrhythmia classification method by applying DL approaches. A DNN with 3-hidden layers is designed for classifying arrhythmia through the MIT-BIH arrhythmia dataset.

3. The Proposed Model

In this article, we have mainly developed an automatic arrhythmia classification algorithm, named AC-DOAEL method on the IoT environment. The presented AC-DOAEL method utilizes IoT-based data collection with an ensemble learning-based classification process. It comprises IoT data collection, ensemble classification, and hyperparameter tuning using DOA. Fig. 1 signifies the workflow of the AC-DOAEL algorithm.

A. IoT Module

IoT network uses a collection of devices including smartwatches, smartphones, sensors, laptops, etc., to promote data exchange and communication between them [19]. The fundamental role is that it is no longer necessary for human interference to exchange data. It chiefly consists of x, the amount of IoT nodes, main station, and cluster heads (CHs). The IoT is signified as Vm, where the x node communicates uniformly within the fa and fb distributed range. IoT node receives a unique ID and the node is collected together and forms a cluster. The cluster made by the IoT node is transferred to the corresponding CHs and the CHs are characterized by the aspect Wz. u shows the amount of CHs and is represented as ($1 \leq z \leq u$). The existing BS from the IoT architecture receives the information from the CHs. the distance between the CHs and BSs is denoted by Dzj and Diz signifies the distance between CHs and IoT nodes. The performance measurement is considered while designing the IoT framework because it is impossible to restore the node existing in the network. Yw characterizes the energy existing at the primary level. Some energy is disseminated while the transmission occurs between the CH nodes and BS. The power dissipation was defined by the energy and the radio electronics transferred via the IoT node are upgraded at BS. At first, the information was attained from the ECG signals through the IoT device that is saved in the BSs. Then, the information from BS is pre-processed and the classification can be implemented.

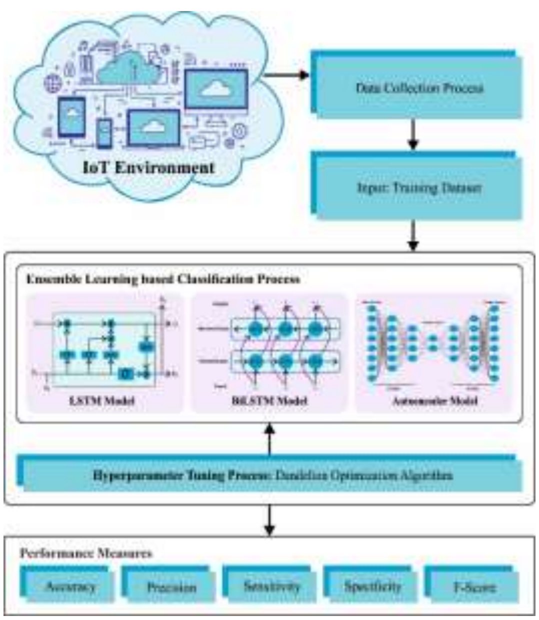

Figure 1: Workflow of AC-DOAEL methodology

B. Ensemble Learning-Based Classification

In this study, the AC-DOAEL technique comprises an ensemble of AE, LSTM, and BiLSTM models for arrhythmia classification. Ensemble classifier combines the outcomes of the multiple DL models to compute a final output.

1) LSTM Model

The RNN produces improved accuracy in modelling the hidden series pattern of time-sequence data [20]. However, during the backpropagation process, the gradient disappearing problems hinder an update of network parameters. Usually, it can be solved by the two different variations of RNN: LSTM and GRU. In theory, the LSTM architecture is similar to RNN; on the other hand, a memory cell was introduced to replace the updating process of RNNs. The memory unit preserves data for a longer time. Assume the present input vector x_t, the last memory cell state c_{t-1}, and the last hidden layer (HL) h_{t-1}, the succeeding expressions are used for executing the LSTM model:

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i) \quad (1)$$

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f\right) \tag{2}$$

$$c_t = f_t c_{t-1} + i_t tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \tag{3}$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o) \tag{4}$$

$$h_t = o_t.tanb(c_t) \tag{5}$$

Now the input gate, forget gate, memory unit, and output gate at t time are represented as i, f, c, and 0 signify. The sigmoid activation function is represented as σ. The weight and bias vector is indicated by W and b.

2) BiLSTM Model

The BiLSTM model is an RNN layer that learns bi-directional long-term dependencies between time steps. Consider historical and future video contexts. Hence, the Bi-LSTM is a convenient alternative in video classification as it retains the information in two directions.

Forward HL $\left(h_t^f\right)$ and backward HL (h_t^b) are the two HLs in BLSTM. The backward HL h_t^b in decreasing order viz., $\mathrm{t = T, T-1, T-2, \dots, 1}$, and forward HL h_t^f consider input vector x_t in increasing order viz., $\mathrm{t} = 1,2,3, \dots, \mathrm{T}$. To sum up, the output y_t is produced by merging h_t^f and h_t^b outcomes. To implement the BiLSTM model, the following equations are used:

$$h_t^f = tanh\left(W_{xh}^f x_t + W_{hh}^f hi_{t-1} + b_h^f\right) \tag{6}$$

$$h_t^b = tanh\left(W_{xh}^b x_t + W_{hh}^b h_{t+1}^b + b_h^b\right) \tag{7}$$

$$y_t = W_{hy}^f h_{\mathrm{t}}^f + W_{hh}^b h_t^b + b_y \tag{8}$$

3) AE Model

The AE is an unsupervised feature representation-learning technique that aims to learn an approximate representation of input by the encoding and decoding layers [21]. Recently, AE has been actively adopted as a multi-label classification model and the most successful DNN. Assume the input as $[x_1, x_2 \dots, x_i \dots, x_n]$, where $x_i \in \Re^m$, the AE attempts to learn an approximate output $h_{W,b}(x) \approx x$. Especially, the AE comprises one encoding and decoding layer correspondingly. In the encoding layer, the input is encoded to multiple hidden layers, and later the hidden layer is decoded to the output as X. The encoding and decoding layer in AE that consists of one HL is formulated as follows:

$$\xi = f(W_1 x + b_1) \tag{9}$$

$$X = g(W_2 \xi + b_2) \tag{10}$$

Where $W_1 \in \Re^{k \times m}$ and $W_2 \in \Re^{m \times k}$ denote the weight matrix, $b_1 \in \Re^{k \times 1}$ and $b_2 \in \Re^{m \times 1}$ are the bias vectors, $\xi \in \Re^{k \times 1}$ show the output of HL, f, and g shows the non-linear activation function of encoding and decoding layers correspondingly. The original input dataset is represented as $\{x_i\}_{i=1}^n$, thereby the reconstructed error is represented as $\sum_{i=1}^n \| \hat{x}_i - x_i \|^2$ The main problem of the AE is to minimize the reconstructed error through the parameter learning about W_1, W_2, b_1, and b_2 that is given below:

$$\min_{W_1, W_2, b_1, b_2} \sum_{i=1}^{n} \| \hat{x}_i - x_i \|^2 \tag{11}$$

C. DOA-based Hyperparameter Tuning

For the hyperparameter selection process, the DOA can be used in this study. The DOA approach has been developed based on the lifecycle of the dandelion plant [22]. The dandelion seed (DSs) is spread through longer distances by the wind. Due to the vortexes above it, the seed structure allows it to travel along the wind that carries the seeds, which lift the DSs during the rising phase. The DSs land in dissimilar locations and gain more weight once the humidity increases or the rain occurs. Few landed seeds might be replanted and used for generating a new generation. The same idea is used for tracking the better outcome of the optimization problem. The ascending, mutation, and selection are three stages of DOA. The aim is to model 3 stages and employ them to search for optimal solutions to optimizer issues.

The optimization method is used to maximize the accuracy of the classification process. The accuracy value is the foremost condition exploited for designing an FF.

$$Fitness = \max(P) \tag{12}$$

$$P = \frac{TP}{TP + FP} \tag{13}$$

Where TP and FP are the true and the false positive values. Dandelion is categorized into two classes: assistant dandelions (ADs) and core dandelions (CDs). The CD has the maximum quantity of power ($P_{\max}$), whereas the ADs are the remaining dandelions.

The mathematical modelling for the breeding cycles of DS is given as follows.

1) Rising Stage

Based on the humidity and the wind speed, a lift force is formed due to the vortices above the DSs, which carry the seed for a distance. The sowing radius of CD signifies the dandelion radius, and it is attained using the following expression.

$$RCD_i^t = \begin{cases} (U - L)/2 \; t = 1 \\ RC_i^{t-1}.e \; a = 1 \\ RC_i^{t-1}.g \; a \neq 1 \end{cases} \tag{14}$$

In Eq. (14), e and g denote the fade and growth factors, correspondingly, the upper and lower limitations of search space are represented as U and L, and a show the factor named the cross trend that is evaluated by.

$$a = \frac{P_{\max}^t + \varepsilon}{P_{\max}^{t-1} + \varepsilon} \tag{15}$$

In Eq. (15), $P_{\max}^{t-1}$ and $P_{\max}^t$ denote the maximal power at prior and existing iterations, correspondingly. ε indicates the tolerance to avoid a denominator being zero.

$$RAD_i^t = \begin{cases} (U - L)/2 & t = 1 \\ \omega.RAD_i^{t-1} + \|d_{CD}^t\| - \|d_{AD}^t\| & Elsewhere \end{cases} \tag{16}$$

In Eq. (16), d_{CD}^t and d_{AD}^t indicate the position of CD and AD of searching agent i at t iteration, correspondingly, ω shows the weight factor which enhances the stability of the searching agent, and it is attained as follows:

$$\omega = 1 - \frac{PE}{PE_{\max}} \tag{17}$$

In Eq. (17), $PEmax$ indicates the overall call counts to the global function throughout the iteration. PE denotes the ratio of the call counts to the objective function to the overall call counts. The inertia factor value given in Eq. (12), begins with 1.0 and slowly drops to 0 if $PE = PE$max. The inertia factor improves the effects of prior radius of AD on the present radius, slowly decreasing these effects, and making it dependent on the difference between the locations of AD and CD.

2) Mutation Sowing

The search particle of AD moves toward the CD-searching agents that search for GP. The mutation method must be applied with the ability of the searching agent to be stuck in the local optima or the CD to avoid premature convergence. Based on the Levy flight, this mutation strategy can be implemented as follows:

$$d_{CD}^t = d_{CD}^t(1 + Levy()) \tag{18}$$

In Eq. (18), Levy () refers to duty ratio values randomly obtained from the LF distribution with β =1.5.

3) Selection Stage

Based on the fitness value, the searching agent must be estimated. In the next iteration, a selection strategy is applied for selecting the searching agent (seeds), and the seeds are detached from the searching agents' swarm size.

$$p_i^t = P_i^t / \sum_{n=1}^{ss^t} P_n^t \tag{19}$$

$$P_i^t = \left| P_i^t - P_{avg}^t \right| \tag{20}$$

Choosing search agents with lower and higher probabilities and eliminating search agents with medium probability to prevent getting stuck in local optima and enhance the DOA's exploration performance. This approach is highly efficient at initial optimizer to enhance exploration and then capturing the location of GP, it eliminates the searching agents with lower probability to optimize the exploitation of DOA. Fig. 2 defines the steps included in DOA.

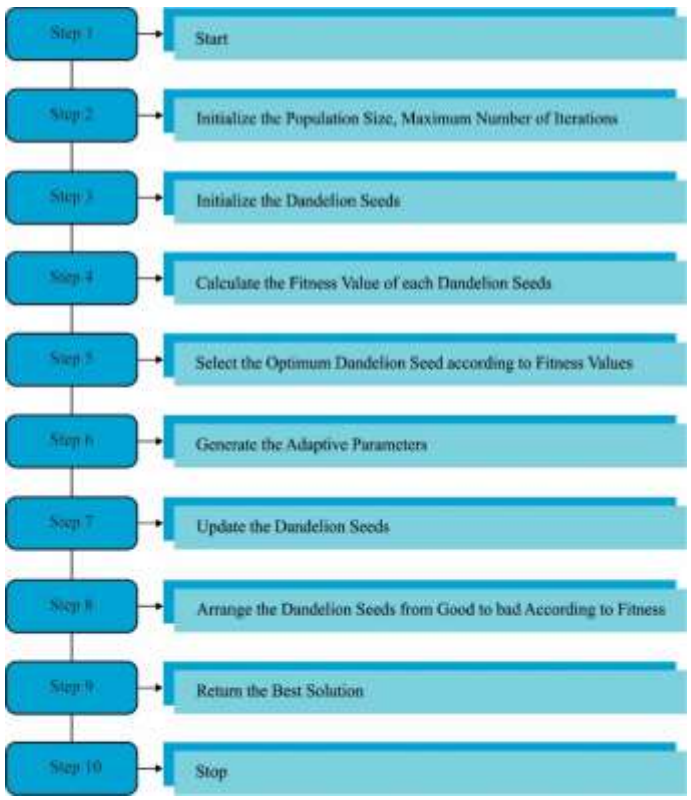

Figure 2: Steps involved in DOA

4. Results and Discussion

The ECG-based arrhythmia classifier outcomes of the AC-DOAEL approach are tested on the PhysioNet dataset [23], involving 12500 samples with the following classes: Normal N (Class-N), Right Bundle Branch Block Beat R (Class-R), Left Bundle Branch Block Beat L (Class-L), Premature Ventricular Contraction V (Class-V), Atrial Premature Beat A (Class-A) as represented in Table 1.

Table 1: Details of database

Super-Class	Annotations	Sub-Classes	No. of Samples
Normal	N	Class-N	2500
Left Bundle Branch Block Beat	L	Class-L	2500
Right Bundle Branch Block Beat	R	Class-R	2500
Atrial Premature Beat	A	Class-A	2500
Premature Ventricular Contraction	V	Class-V	2500
Total Number of Samples			12500

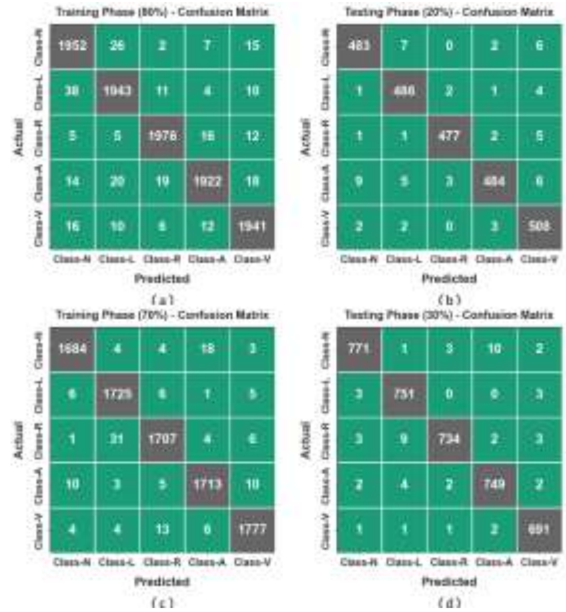

Figure 3: Confusion matrices of (a-b) 80:20 of TR set (TRST)/TS set (TSST) and (c-d) 70:30 of TRST/TSST

Fig. 3 demonstrates the confusion matrices attained by the AC-DOAEL method at 80:20 and 70:30 of the TRST/TSST. The simulation value referred to the detection and classification of five classes.

The classifier outcomes of the AC-DOAEL algorithm are investigated at 80:20 of the TRST/TSST as shown in Table 2 and Fig. 4. The result highlights the proficient detection of five class labels by the AC-DOAEL technique. With an 80% TRST, the AC-DOAEL method provides an average $accu_y$ of 98.94%, $prec_n$ of 97.34%, $sens_y$ of 97.34%, $spec_y$ of 99.34%, and F_{score} of 97.34%. Besides, with a 20% TSST, the AC-DOAEL method obtains an average $accu_y$ of 99.01%, $prec_n$ of 97.55%, $sens_y$ of 97.52%, $spec_y$ of 99.38%, and F_{score} of 97.53%.

Table 2: Classifier outcomes of AC-DOAEL method on 80:20 of TRST/TSST

Class Labels	$Accu_y$	$Prec_n$	$Sens_y$	$Spec_y$	F_{Score}
TRST (80%)					
Class-N	98.77	96.40	97.50	99.09	96.95
Class-L	98.76	96.96	96.86	99.24	96.91
Class-R	99.24	98.11	98.11	99.52	98.11
Class-A	98.90	98.01	96.44	99.51	97.22
Class-V	99.01	97.24	97.78	99.31	97.51
Average	98.94	97.34	97.34	99.34	97.34
TSST (20%)					
Class-N	98.88	97.38	96.99	99.35	97.18
Class-L	99.08	97.01	98.38	99.25	97.69
Class-R	99.44	98.96	98.15	99.75	98.55
Class-A	98.76	98.37	95.46	99.60	96.90
Class-V	98.88	96.03	98.64	98.94	97.32
Average	99.01	97.55	97.52	99.38	97.53

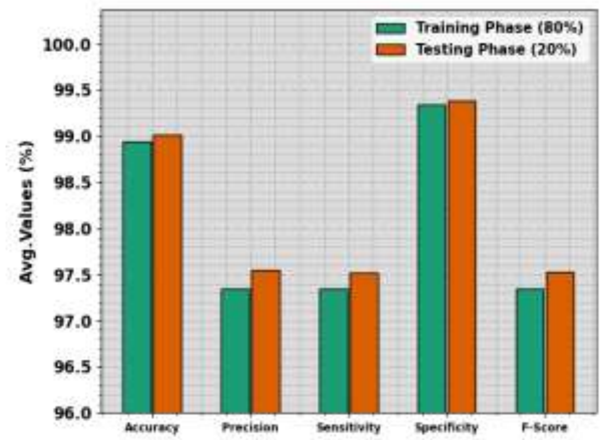

Figure 4: Average of AC-DOAEL method on 80:20 of TRST/TSST

The classifier outcome of the AC-DOAEL system is examined at 70:30 of the TRST/TSST as shown in Table 3 and Fig. 5. The outcome depicted the proficient detection of five class labels by the AC-DOAEL method. With a 70% TRST, the AC-DOAEL system achieves an average $accu_y$ of 99.34%, $prec_n$ of 98.36%, $sens_y$ of 98.35%, $spec_y$ of 99.59%, and F_{score} of 98.35%. Besides, with a 30% TSST, the AC-DOAEL method obtains an average $accu_y$ of 99.42%, $prec_n$ of 98.56%, $sens_y$ of 98.57%, $spec_y$ of 99.64%, and F_{score} of 98.57%.

Table 3: Classifier outcomes of AC-DOAEL method on 70:30 of TRST/TSST

Class Labels	$Accu_y$	$Prec_n$	$Sens_y$	$Spec_y$	F_{Score}
TRST (70%)					
Class-N	99.43	98.77	98.31	99.70	98.54
Class-L	99.31	97.62	98.97	99.40	98.29
Class-R	99.20	98.39	97.60	99.60	97.99
Class-A	99.35	98.34	98.39	99.59	98.36
Class-V	99.42	98.67	98.50	99.65	98.59
Average	99.34	98.36	98.35	99.59	98.35
TSST (30%)					
Class-N	99.33	98.85	97.97	99.70	98.40
Class-L	99.44	98.04	99.21	99.50	98.62
Class-R	99.39	99.19	97.74	99.80	98.46
Class-A	99.36	98.17	98.68	99.53	98.42
Class-V	99.60	98.57	99.28	99.67	98.93
Average	99.42	98.56	98.57	99.64	98.57

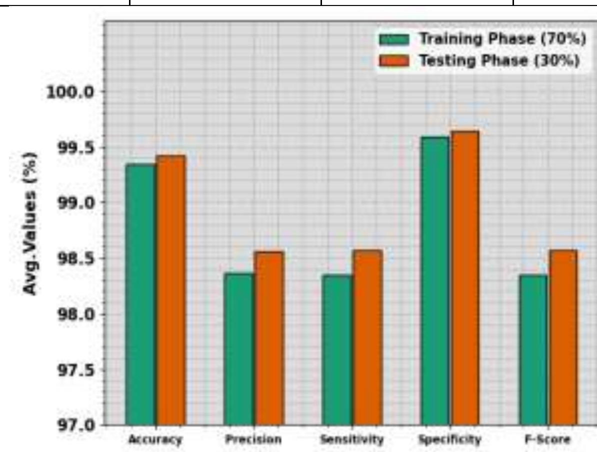

Figure 5: Average of AC-DOAEL method on 70:30 of TRST/TSST

Fig. 6 defines the TR_accu_y and VL_accu_y of the AC-DOAEL algorithm at 70:30 of the TRST/TSST. The TL_accu_y is calculated by assessing the AC-DOAEL system on the TR dataset while the VL_accu_y is determined by the estimation of the performance on a testing dataset. The outcomes display that TR_accu_y and VL_accu_y increased with the increasing number of epochs. Consequently, the performance of the AC-DOAEL technique gets enhanced on the TR and TS datasets with an upsurge in epochs.

Figure 6: $Accu_y$ curve of AC-DOAEL method on 70:30 of TRST/TSST

In Fig. 7, the TR_loss and VR_loss outcome of the AC-DOAEL technique on 70:30 of the TRST/TSST is exposed. TR_loss determines the error among the original values and predictive outcomes on the TR dataset. The VR_loss represents the performance measure of the AC-DOAEL system on validation data. The outcome demonstrates that TR_loss and VR_loss tend to decrease with rising epochs. It depicted the better outcome of the AC-DOAEL technique and its capability to create an accurate classification. The minimal value of TR_loss and VR_loss illustrates the greater solution of the AC-DOAEL technique for capturing relationships and patterns.

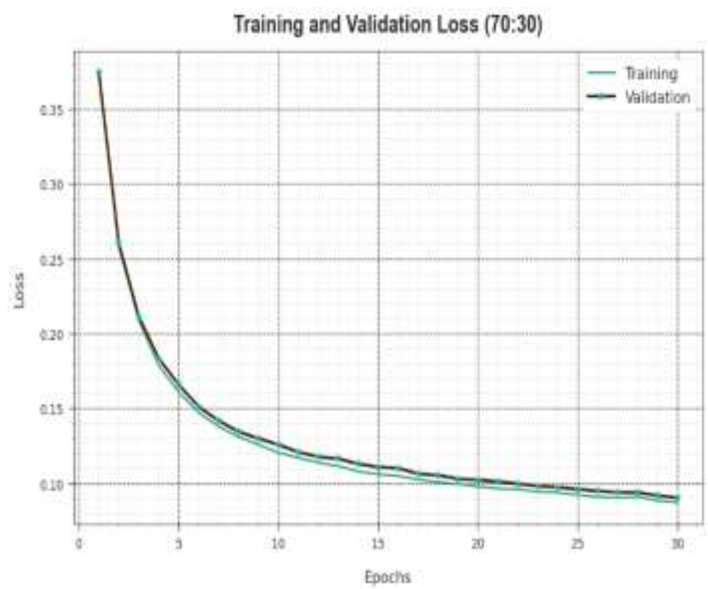

Figure 7: Loss curve of AC-DOAEL method on 70:30 of TRST/TSST

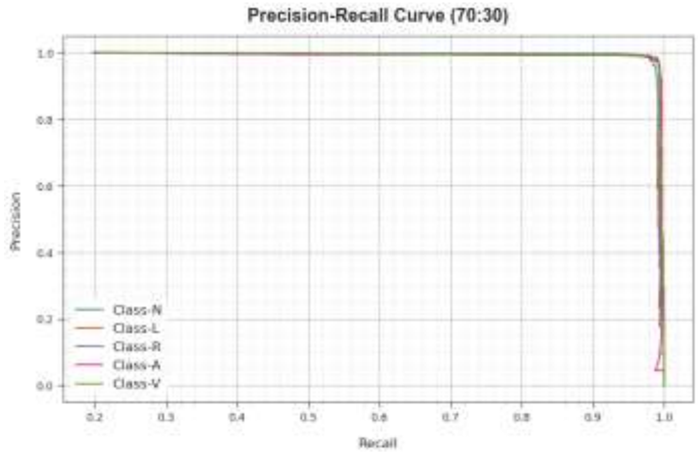

Figure 8: PR curve of AC-DOAEL method on 70:30 of TRST/TSST

A comprehensive PR study of the AC-DOAEL system is depicted at 70:30 of the TRST/TSST in Fig. 8. The outcome values showed that the AC-DOAEL method performs in high PR values. Next, the AC-DOAEL technique obtains better values of PR in 5 classes.

In Fig. 9, a ROC analysis of the AC-DOAEL system is defined at 70:30 of the TRST/TSST. The simulation value demonstrated that the AC-DOAEL system led to superior values of ROC. Afterward, it can be clear that the AC-DOAEL method achieves higher performances of ROC on 5 classes.

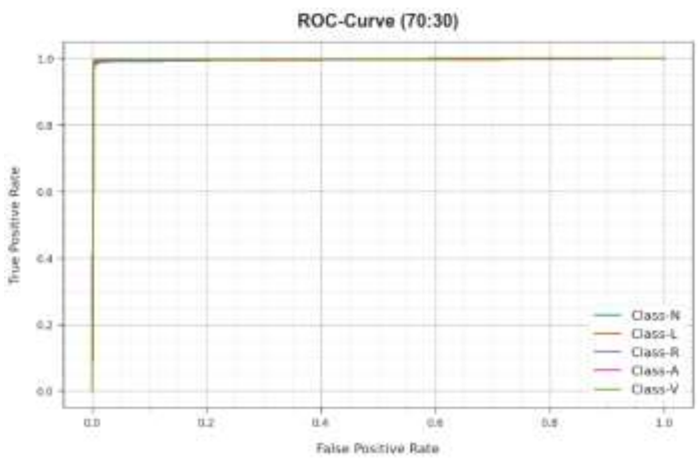

Figure 9: ROC of AC-DOAEL method on 70:30 of TRST/TSST

The comparative results of the AC-DOAEL approach on the arrhythmia classification are given in Table 4 [19, 24]. The results indicate that the deep LSTM, LSTM, BiLSTM, and DCNN models have portrayed ineffectual classification results. Along with that, the Deep 1D-CNN model has shown moderate outcomes over earlier models. Although the HCAD-M-DL model reaches near-optimal results, the AC-DOAEL technique surpassed the existing ones with maximum $accu_y$, $prec_n$, $sens_y, spec_y$, and F_{score} of 99.42%, 98.56%, 98.57%, 99.64%, and 98.57% correspondingly. These outcomes highlighted the effectual classification of the AC-DOAEL method.

Table 4: Comparative outcome of AC-DOAEL approach with other methods

Approach	$\boldsymbol{Accu_y}$	$\boldsymbol{Prec_n}$	$\boldsymbol{Sens_y}$	$\boldsymbol{Spec_y}$	$\boldsymbol{F_{Score}}$
Deep LSTM	95.80	96.24	97.85	96.38	94.53
LSTM Model	95.00	97.03	97.85	96.83	95.99
BiLSTM Model	95.00	97.51	96.58	96.93	95.07
DCNN Algorithm	94.00	96.90	96.58	97.72	94.82
Deep 1D-CNN	97.00	96.17	97.85	95.38	95.13
HCAD-M-DL	99.30	97.72	97.85	96.35	97.33

AC-DOAEL	99.42	98.56	98.57	99.64	98.57

5. Conclusion

In this article, we have mainly developed an automatic arrhythmia classification approach, named AC-DOAEL technique on the IoT platform. The presented AC-DOAEL method utilizes IoT-based data collection with an ensemble learning-based classification process. It comprises IoT data collection, ensemble classification, and hyperparameter tuning using DOA. For the arrhythmia detection and classification process, the AC-DOAEL technique follows an ensemble learning approach comprising LSTM, AE, and BiLSTM models. To improve the recognition rate of the ensemble models, the AC-DOAEL technique uses DOA as a hyperparameter optimizer. The simulation outcomes of the AC-DOAEL method are well-studied on benchmark ECG data. The simulation values showed the great outcomes of the AC-DOAEL technique with other models. In the upcoming work, the performance of the AC-DOAEL method is increased by the metaheuristic feature selection approach.

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