Received: 20 May 2023 | Revised: 12 July 2023 | Accepted: 15 July 2023
DOI: 10.37917/ijeee.20.1.10 Vol. 20 | Issue 1 | June 2024

Open Access

Iraqi Journal for Electrical and Electronic Engineering
Original Article

IJ EEE University of Basrah College of Engineering

Recognition of Cardiac Arrhythmia using ECG Signals and Bio-inspired AWPSO Algorithms

Jyothirmai Digumarthi[1], **V. M. Gayathri**[*2], **R. Pitchai**[3]
[1]Department of Networking and Communications , Faculty of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, Tamilnadu, India.
[2]Department of Networking and Communications, Faculty of Engineering and Technology, SRM Institute of Science and Technology, Kattankulathur, Tamilnadu, India.
[3]Department of Computer Science and Engineering, B V Raju Institute of Technology, Narsapur, Telagana, India

Correspondence
* V. M. Gayathri
School of Computing, SRM Institute of Science and Technology
Tamilnadu, India
Email: gayathrm@srmist.edu.in

Abstract
Studies indicate cardiac arrhythmia is one of the leading causes of death in the world. The risk of a stroke may be reduced when an irregular and fast heart rate is diagnosed. Since it is non-invasive, electrocardiograms are often used to detect arrhythmias. Human data input may be error-prone and time-consuming because of these limitations. For early detection of heart rhythm problems, it is best to use deep learning models. In this paper, a hybrid bio-inspired algorithm has been proposed by combining whale optimization (WOA) with adaptive particle swarm optimization (APSO). The WOA is a recently developed meta-heuristic algorithm. APSO is used to increase convergence speed. When compared to conventional optimization methods, the two techniques work better together. MIT-BIH dataset has been utilized for training, testing and validating this model. The recall, accuracy, and specificity are used to measure efficiency of the proposed method. The efficiency of the proposed method is compared with state-of-art methods and produced 98.25 % of accuracy.

Keywords
Cardiac Arrhythmia; Whale optimization; Meta-heuristic algorithm; Electrocardiogram; Diagnose.

I. Introduction

The World Health Organization says that cardiovascular disease (CVD) will still be the leading cause of death around the world until 2030. An estimated 17.5 million people die each year as a result of CVD, accounting for 31 % of all deaths [1]. More than 75 % of all deaths from CVD occur in countries with a per capita income below the world average. It is estimated that heart attacks and strokes account for 80 % of all cardiovascular disease deaths. Therefore, long-term repercussions from cardiac arrhythmias occurring inside the heart are responsible for these problems and must be recognized early on in order to have an appropriate diagnosis.The electrocardiographic (ECG) analysis is a frequent noninvasive diagnostic technique in clinical cardiology. ECG analysis has led to improved therapy and earlier identification of potentially fatal cardiac arrhythmias. In reality, a cardiologist's event-by-event review may be laborious and time-consuming. An automated diagnosis of heart signals that can help clinicians in providing the necessary medical care to patients. Consequently, the study of ECG signals using different modeling methods has grown into a current research topic on which this paper focuses. To extract features from ECG signals, some of these approaches include temporal domain analysis; statistical approaches, hybrid features, frequency-based analysis, and time-frequency analysis have been utilized. It is possible to identify and classify cardiac anomalies using these feature extraction methods and a variety of classification algorithms such as linear discriminants neural networks, neuro-fuzzy approach, and support vector machines [2–7]. Hybridization is a novel idea in optimization that combines two meta-heuristic algorithms. Combining whale optimization (WOA) with adaptive particle swarm optimization (APSO), a hybrid bio-inspired algorithm is designed to choose the best characteristics. The ECG signal is processed in this way to extract the most useful information. The WOA is a recently developed meta-heuristic algorithm [8]. Fewer parameters, a wider search area and more efficient investigation are just some of the benefits. APSO is used to increase convergence speed while also ensuring that the search area is used and explored in a balanced manner [9]. When compared to ordinary optimization methods, the two techniques work better together. As a result, AWPSO, a mix of WOA and APSO, is created for feature selection in this study as well. This paper is organized as follows. The literature review is presented in Section 2. The suggested framework is fully explored in Section 3. Then the preliminary findings and numerical performance measures are presented in Section 4. Finally, the conclusion and future avenues are presented in Section 5.

II. Related Works

Intelligent classification models for the identification of cardiac arrhythmias have been built using a machine learning methodology. Arrhythmia detection using convolution and deep neural network approaches has recently been presented [10–13]. There are a number of different strategies that have been used to improve the accuracy of data sets like MIT BIH. Machine learning approaches were used in other recent research to categories 16 distinct arrhythmias based on the ECG data [14–16]. Support vector machine (SVM) classification of ECG waveform arrhythmia was suggested to be trained through genetic bat optimization [17]. It was utilized to verify and categories the heartbeat rate using the wavelet-based method and Gabor filters. Heartbeat characteristics may be extracted and classification algorithms can be used to identify arrhythmias, depending on the categorization. Fast ECG diagnosis was made possible using the radio frequency models [18]. The accuracy was found to be adequate. To identify arrhythmia from ECG data, most researchers used Convolution neural network (CNN) in conjunction with Long short-term memory (LSTM) and were improved the accuracy. In order to detect arrhythmic heartbeats, the deep CAE-LSTM approach was developed in [19]. ECG waves were shortened and low-dimensional digitized information was collected from individual ECG recordings using this technology specifically. An LSTM network model was used to classify the coded signals. An ECG classification method based on deep learning was used to automatically categories six ECG signal types. A multi-input structure was used to analyse ECG records and their associated length from the well-known MIT-BIH data set. An attention module categorized eight groups of arrhythmias and sinus rhythms from ECG data in two stages: spatial information fusion using CNNs and temporal information fusion using LSTM cells [20]. For detecting myocardial infarction using ECG data, a hybrid CNN-LSTM model and ensemble approach was developed [21]. It was found that identifying all non-MI beats as regular and all myocardial infarction (MI) beats as MI beats yielded good results. ECG data may be used to automatically diagnose cardiac arrhythmias using multi-layer probabilistic neural network (MPNN). A CNN-Bi-LSTM approach for arrhythmia classification is currently absent, despite the fact that there has been a lot of work done in this area. Bio-inspired algorithm has recently been applied in a variety of applications and has performed well. The main contribution of this paper is to develop a bio-inspired algorithm to identifying cardiac arrhythmia.

A. Background

When an ECG is used as a non-invasive diagnostic technique, it provides a visual representation of the heart's electrical activity. One of the most common symptoms of arrhythmia is a rapid or sluggish pulse that may be caused by a variety of cardiac conditions [22]. DNNs have recently been used in the classification of ECG data. Using sufficient training data, a DNN model can recover more features than a human approach can. In majority of the artificial intelligence applications use sequential data, the CNN and bio-inspired algorithms are frequently used for prediction, detection, and identification [23]. Because of its reprocate characteristics, CNN is an effective feature extraction approach. Both CNN and bio-inspired algorithms are better at identifying multi-class arrhythmias than the previous methods.

B. MIT-BIH ARRHYTHMIA DATABASE

There has been an increase in interest in the MIT-BIH dataset in the last several years. Since 1980, this data collection has been used to undertake fundamental cardiac dynamics research at more than 500 sites throughout the world. 42 Arrhythmia data from MIT-public BIH's PhysioNet arrhythmia database is used in the proposed method. To capture the whole 10 mV voltage range, the data was sampled at 360 samples per second. A sampling rate of 360 Hz was utilized to sample the signals. Small text files called "header files" (.hea) include information about the signals, such as their name, sample size, recording type (with time stamps), and other pertinent clinical information. One or more signals in the record are labelled in an annotation file, and each label describes a feature of that signal.

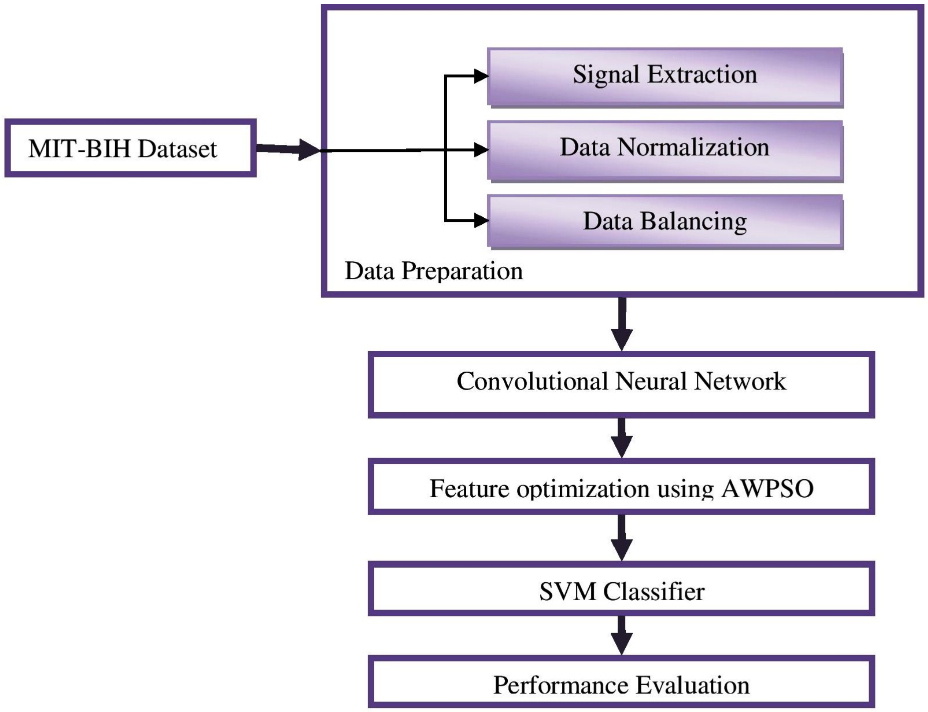

Fig. 1. Proposed Block diagram

III. PROPOSED METHODOLOGY

The proposed block diagram is shown in Fig. 1. Before the MIT-BIH data set can be used to train a model, signal extraction, data standardization, and data balancing must be done. The ECG signals are split during the training, validation, and testing steps. With the re-sampling method, the training data are made fair by giving more samples to the minority classes and less to the majority classes. The first step in developing a model is to make a CNN model with the right number of layers, filters, kernel sizes, and activation functions. CNN is used to get the attribute information. Then, the AWPSO algorithm and the CNN model are put together. The results are then compared to each other as an extra test to make a reliable model.

A. AWPSO Algorithm

The steps involved in the AWPSO algorithm are briefly given in Fig. 2. The search agents, on the other hand, alter their positions in response to particular agent behaviour The objective function Fit_{ob} is utilized for every iteration, and it is described in the following equation (1),

$$Fit_{ob} = E*(1+\beta)/RF \tag{1}$$

$$RF = m/S$$

Here, E represents the overall error, b is a constant $(0.5), m$ indicates the number of chosen features, and S indicates the number of swarms.

Table I shows the tributes utilized in the hybrid bio-inspired algorithm. The hunting function is carried out with the assistance of the best search agent, which follows the location of the prey to surround it. This operation is expressed as equations (2 and 3),

$$\overrightarrow{E} = |\overrightarrow{L}.\overrightarrow{Y^*}(i) - \overrightarrow{Y}(i)| \tag{2}$$

$$(i+1) = \overrightarrow{Y^*}(i) - P.\overrightarrow{E} \tag{3}$$

L and P represents the coefficient vectors (CV), i is the current iteration, $\overrightarrow{Y}$ is the position vector and $\overrightarrow{Y^*}(i)$ is the position vector of the best solution acquired. The CV is represented by the equation (4),

$$P = 2b.r - b \tag{4}$$

$$L = 2.r$$

Where, b is linearly decreasing from 2 to 0 and r is random vector $[0,1]$. The whales and prey function is given in equation (5),

$$Y(i+1) = E.e^{al}cos(2\pi l) + Y^*(i) \tag{5}$$

TABLE I.
PARAMETERS AND VALUES USED FOR AWPSO ALGORITHM

Parameter	Values
Lb	1
Ub	160
Dim	20
Maxiteration	35
Gamma	0.5
Search Agents no	25

The prey change its position by the following equation (6), Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Ut purus elit, vestibulum ut, placerat ac, adipiscing vitae, felis. Curabitur dictum gravida mauris. Nam arcu libero, nonummy eget, consectetuer id, vulputate a, magna. Donec vehicula augue eu neque. Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Mauris ut leo. Cras viverra metus rhoncus sem. Nulla et lectus vestibulum urna fringilla ultrices. Phasellus eu tellus sit amet tortor gravida placerat. Integer sapien est, iaculis in, pretium quis, viverra ac, nunc. Praesent eget sem vel leo ultrices bibendum. Aenean faucibus. Morbi dolor nulla, malesuada eu, pulvinar at, mollis ac, nulla. Curabitur auctor semper nulla. Donec varius orci eget risus. Duis nibh mi, congue eu, accumsan eleifend, sagittis quis, diam. Duis eget orci sit amet orci dignissim rutrum.

$$\overrightarrow{Y}(i+1) = \left[C^{i}_{rj} * v^{i+1}\right] + \left[f_1 * v^{i}_{1j} * (R^{r}_{Best,r} - x^{i}_{rj})\right] + \left[f_2 * v^{i}_{2j} * (R^{r}_{Best,r} - x^{i}_{rj})\right]$$

Here, R_{best} represents the local best search

$$y_{rj}(i+1) = y_{rj}(i+1) + fa * C_{rj}(i+1) \tag{6}$$

$$G_{best} = G_{best} + G_a = G_{best} + (max(y_j) - min(y_j) \times rand$$

Here, fa is Adaptive factor and G_{best} global best location. The CV cab be modified as equation (7),

$$\overrightarrow{Y}(i+1) = \overrightarrow{Y_{random}} - \overrightarrow{P}.\overrightarrow{E} \tag{7}$$

The computational time complexity of the suggested algorithm could be determined by using the following equation (8),

$$T(n) = 2n + s + nlog(n).t = O(nlog(n).t) \tag{8}$$

The computational time of this proposed method is about 0.4s. To reduce the number of dimensions and choose the best-optimized subgroups, linear discriminant analysis is used to execute feature selection grouping.

SVM is a maximal margin classifier which is given in Fig. 3. By constructing the hyper plane, it categorizes the data. It works better for categorizing binary classes. It is also used for solving multiclass issues. There are two types of SVM classifications are there namely one-vs-one (OvO) and one-vs-rest (OvR). In this paper, OvR SVM classification is used.
In this article, a polynomial kernel of degree 3 is utilized. Parameter 'C', also known as the cost parameter, determines the permissible degree of misclassification. Greater values of 'C' result in the selection of a hyper plane with a narrower margin. Smaller values of 'C', on the other hand, require the classifier to seek a larger margin, even if the hyper plane misclassifies the points. Generally, a high 'C' value is desirable, although it may result in overfitting. The kernel breadth parameter () modifies the shape of the class-dividing line. When it is high, only points near to the hyperplane are taken into consideration. When is low, distant points from the hyper plane are taken into account. In general, it is preferable to have a small value of, as a larger number may lead to overfitting.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

A. *Performance matrices*

The different performance matrices such as accuracy, recall, precision, and specificity of the proposed model are evaluated. With true positive (TP), true negative (TN), false positive (FP), false negative (FN), the parameters are described as follows,
Accuracy: Accuracy is the degree to which the result of a measurement matches the correct value.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{9}$$

Recall: Sensitivity quantifies the reliability with which a test returns a positive result for those who have tested positive for the illness.

$$Recall = \frac{TP}{TP+FN} \tag{10}$$

Precision:It is a fact of being exact and accurate.

$$Precision = \frac{TP}{TP+FP} \tag{11}$$

Specificity: Describes a test ability to consistently return a negative result for those whose condition has not been examined.

$$Specificity = \frac{TN}{FP+TN} \tag{12}$$

In Table II, each column demonstrates the number of ECG beats that are detected using the proposed method, and each

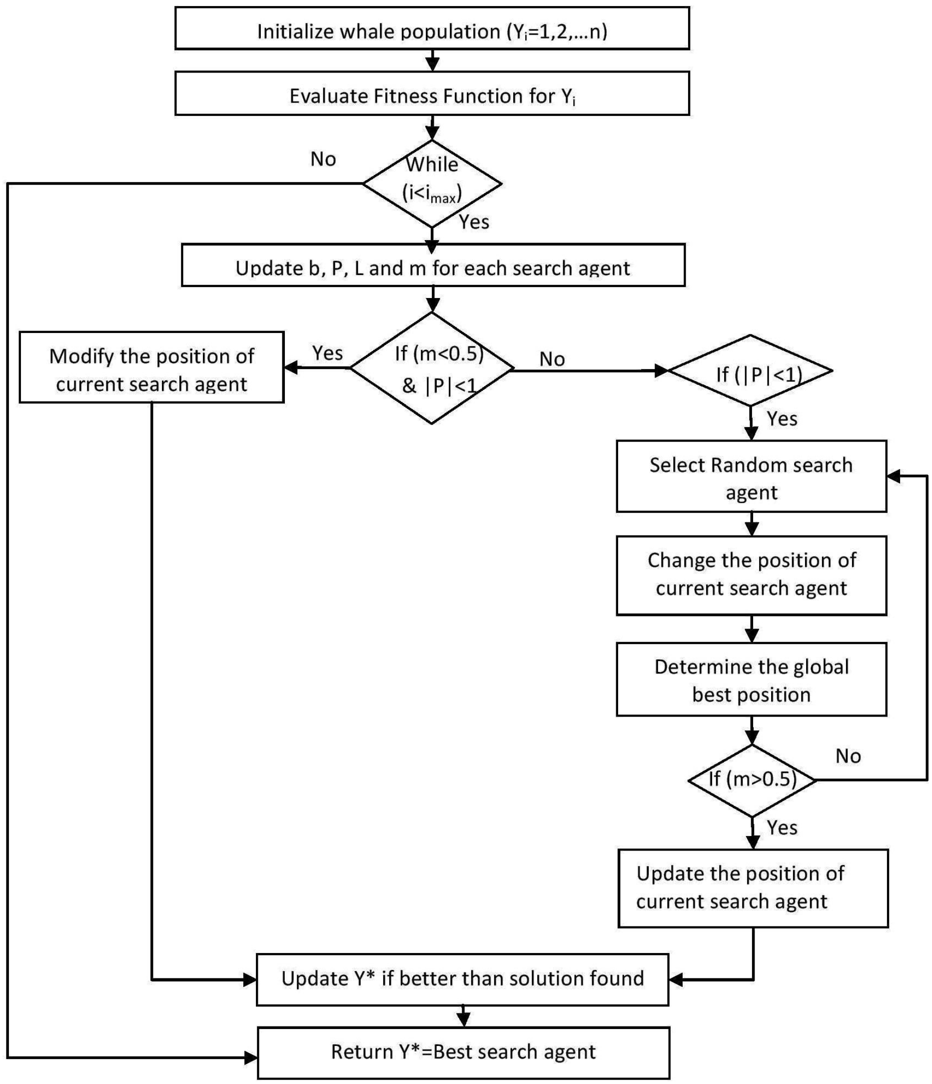

Fig. 2. AWPSO Algorithm

row demonstrates the number of signals that are really annotated at the database. Additionally, the performance parameters for each type of cardiac signal, such as TP, FP, and FN, are computed and shown for clarity. The dataset has 16 different classes. Totally, it has 110109 beats, in that 55051 is used for training and 55058 beats are used for testing. Row 2 of this table is devoted to the left bundle branch block (LBBB) category, and within that row, we can see that 37294 of the 75017 LBBB signals have been properly classified. On the other hand, the distinctions between the signals are not placed in the appropriate category. Out of the 55058 beats that are examined using the category-based approach, there are 54420 signals that are accurately categorised.

According to these numbers, the suggested approach has an accuracy of 98.84 % and an error rate of 1.16 %. On their own, the symmetrical characteristics contributed to a classification accuracy rate of 98.95 %. In the similar manner, the other classes also classified and tabulated. In-depth research is conducted on the positive predictivity evaluation parameters and the sensitivity evaluation parameters based on these factors. According to Table II, the unclassifiable beat (UN) exhibited a sensitivity that was very low at just 40 percent while having an extremely high positive predictivity of 92.13, while the ventricular escape (VE) beat had the greatest degree of sensitivity as well as positive predictivity, both of which were 100 %. The confusion matrix of cross validation is given in Table III.

Table IV summaries the overall performance of the proposed

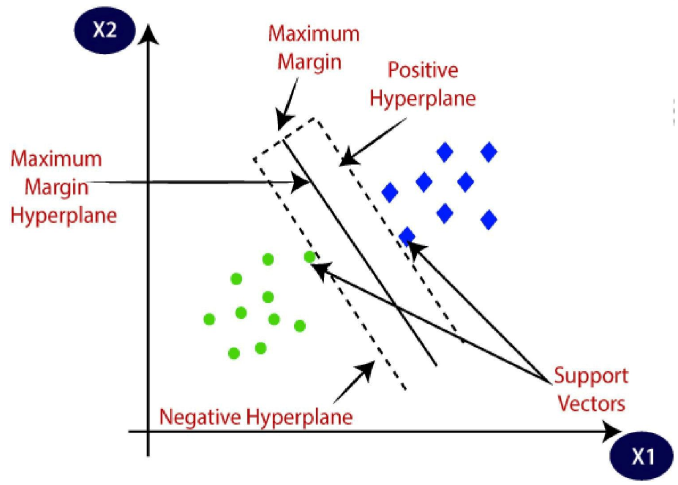

Fig. 3. Support Vector Machine

TABLE II.
PERFORMANCE ASSESSMENT OF DIFFERENT CLASSES OF CARDIAC SIGNAL

Heartbeat Class	Total	Trained Beats	Test Beats	FN	TP	FP	PR	RE
N	75017	37508	37509	215	37294	87	99.77	99.43
L	8072	4036	4036	135	3901	68	98.29	96.66
R	7255	3627	3628	89	3539	23	99.35	97.55
A	2546	1273	1273	45	1228	98	92.61	96.47
V	7129	3564	3565	69	3496	48	98.65	98.06
P	7024	3512	3512	31	3481	112	96.88	99.12
a	150	75	75	1	74	3	96.10	98.67
!	472	236	236	5	231	21	91.67	97.88
F	802	401	401	18	383	45	89.49	95.51
x	193	96	97	3	94	14	87.04	96.91
j	229	114	115	9	106	5	95.50	92.17
f	982	491	491	12	479	32	93.74	97.56
E	106	53	53	2	51	9	85.00	96.23
J	83	41	42	4	38	4	90.48	90.48
e	16	8	8	0	8	0	100.00	100.00
Q	33	16	17	0	17	0	100.00	100.00
Total/Avg	**110109**	**55051**	**55058**	**638**	**54420**	**569**	**94.66**	**97.04**

TABLE III.
CONFUSION MATRIX OF CROSS-VALIDATION

Predicted Label						
Class	**N**	**S**	**v**	**F**	**Q**	**TN**
N	85521	1258	3655	4166	81	8651
S	595	1157	501	35	11	1254
V	452	266	6874	325	39	1035
F	384	41	425	635	26	598
Q	10	5	56	5	5	76

method. For training, testing, and validation, the various parameters such as Accuracy, Recall, Precision, and Specificity are calculated and tabulated. The proposed procedure has an Accuracy of 98.95%, a Recall of 98.32%, a Precision of 92.15%, and a Specificity of 91.98%. In addition, the performance of the proposed method is compared to that of state-of-the-art methods in Table V. Figure 4 represents the graphical analysis. There is a correlation between the proposed method and eight other methodologies. By analyzing the table, we can conclude that neither the CNN nor RNN+LSTM models have undergone pre-processing.

TABLE IV.
OVERALL PERFORMANCE PARAMETERS

Performance Parameters	MIT-BIH dataset		
	Train values	**Validation**	**Testing**
Accuracy	100	98.21	98.95
Recall	100	94.45	98.32
Precision	100	89.48	92.15
Specificity	99.44	94.75	91.98

TABLE V.
COMPARATIVE ANALYSIS WITH STATE-OF-THE-ART METHODOLOGIES

Methodology	**Preprocessing**	**Classes**	**Accuracy (%)**	**Specificity (%)**	**Recall (%)**
11 Layers CNN	Yes	4	92.50	93.10	98.06
9 Layers CNN	Yes	5	94.03	91.54	94.03
CNN-LSTM	Yes	5	98.10	98.70	97.50
CNN	No	5	93.71	94.77	91.25
CNN+LSTM	Yes	6	96.62	96.80	95.40
WKNN	Yes	4	96.12	99.40	83.35
RNN+LSTM	No	2	88.10	92.40	83.35
Ensemble SVMs	Yes	4	94.05	92.96	92.84
Proposed Method	**Yes**	**4**	**98.25**	**91.98**	**98.32**

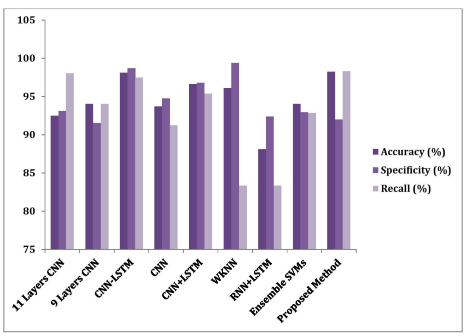

Fig. 4. Graphical Analysis of State-of-art-Methodology

These existing methodologies classified different number of classes. The 11 layers CNN method classified 4 different classes and gives the accuracy of 92.50% with the specificity of 93.10% and Recall of 98.06%.Where as, the 9 layers of CNN classified 5 different classes with the accuracy of 94.03%, specificity of 91.54 and recall of 94.03. After analyzing these two methods, accuracy is closely related to the number of layers used in the CNN. When the number of layers increases, the accuracy gets decreased. In order to improve the accuracy, the CNN is combined with LSTM. The CNN-LSTM method improved the accuracy to 98.10%, specificity of 98.70% and recall of 97.50%. For further improvement of performance, in the proposed method, bio-inspired algorithm is combined with the CNN and gives the accuracy of 98.25%, specificity of 91.98% and the recall of 98.32%.

V. CONCLUSIONS

Cardiovascular disease may be reduced if irregular heartbeats are detected and treated early. The main aim of this study is to quickly detecting the kind of ECG or establishing a medical diagnosis. Training, validation, and testing on the MIT-BIH data set yielded maximum accuracies of 100%, 98.21%, and 98.95% respectively. ECG recordings may help clinicians make better decisions regarding patient care, and this research showed that it can do so. As a result, it is developed to be the most user-friendly and efficient while yet delivering the greatest results. The method described here is straightforward for medical practitioners to use since no signal modification is required. The symptoms of cardiac sickness are typically complex and vary, and this research solely focused on arrhythmia, which is a kind of CVD. As a result, the network's potential will be enhanced by adding new types of ECG data.

CONFLICT OF INTEREST

The authors have no conflict of relevant interest to this article.

REFERENCES

[1] W. H. Organization *et al.*, "Weekly epidemiological record, 2013, vol. 88, 35 [full issue]," *Weekly Epidemio-*

logical Record= Relevé épidémiologique hebdomadaire, vol. 88, no. 35, pp. 365–380, 2013.

[2] Q. H. Nguyen, B. P. Nguyen, T. B. Nguyen, T. T. Do, J. F. Mbinta, and C. R. Simpson, "Stacking segment-based cnn with svm for recognition of atrial fibrillation from single-lead ecg recordings," *Biomedical Signal Processing and Control*, vol. 68, p. 102672, 2021.

[3] P. Shimpi, S. Shah, M. Shroff, and A. Godbole, "A machine learning approach for the classification of cardiac arrhythmia," in *2017 international conference on computing methodologies and communication (ICCMC)*, pp. 603–607, IEEE, 2017.

[4] S. Sahoo, M. Dash, S. Behera, and S. Sabut, "Machine learning approach to detect cardiac arrhythmias in ecg signals: A survey," *Irbm*, vol. 41, no. 4, pp. 185–194, 2020.

[5] N. A. Trayanova, D. M. Popescu, and J. K. Shade, "Machine learning in arrhythmia and electrophysiology," *Circulation research*, vol. 128, no. 4, pp. 544–566, 2021.

[6] R. Vani, B. Sowmya, S. Kumar, G. Babu, and R. Reena, "An adaptive fuzzy neuro inference system for classification of ecg cardiacarrthymias," in *AIP Conference Proceedings*, vol. 2393, AIP Publishing, 2022.

[7] F. Melgani and Y. Bazi, "Classification of electrocardiogram signals with support vector machines and particle swarm optimization," *IEEE transactions on information technology in biomedicine*, vol. 12, no. 5, pp. 667–677, 2008.

[8] N. Li, F. He, W. Ma, R. Wang, L. Jiang, and X. Zhang, "The identification of ecg signals using wavelet transform and woa-pnn," *Sensors*, vol. 22, no. 12, p. 4343, 2022.

[9] E. H. Houssein, M. A. Mahdy, D. Shebl, and W. M. Mohamed, "A survey of metaheuristic algorithms for solving optimization problems," in *Metaheuristics in machine learning: theory and applications*, pp. 515–543, Springer, 2021.

[10] Y. Zhang, S. Liu, Z. He, Y. Zhang, and C. Wang, "A cnn model for cardiac arrhythmias classification based on individual ecg signals," *Cardiovascular Engineering and Technology*, pp. 1–10, 2022.

[11] H. M. Rai and K. Chatterjee, "Hybrid cnn-lstm deep learning model and ensemble technique for automatic detection of myocardial infarction using big ecg data," *Applied Intelligence*, vol. 52, no. 5, pp. 5366–5384, 2022.

[12] M. N. Meqdad, F. Abdali-Mohammadi, and S. Kadry, "A new 12-lead ecg signals fusion method using evolutionary cnn trees for arrhythmia detection," *Mathematics*, vol. 10, no. 11, p. 1911, 2022.

[13] M. S. Islam, M. N. Islam, N. Hashim, M. Rashid, B. S. Bari, and F. Al Farid, "New hybrid deep learning approach using bigru-bilstm and multilayered dilated cnn to detect arrhythmia," *IEEE Access*, vol. 10, pp. 58081–58096, 2022.

[14] S. B. Itzhak, S. S. Ricon, S. Biton, J. A. Behar, and J. A. Sobel, "Effect of temporal resolution on the detection of cardiac arrhythmias using hrv features and machine learning," *Physiological Measurement*, vol. 43, no. 4, p. 045002, 2022.

[15] F. K. Wegner, L. Plagwitz, F. Doldi, C. Ellermann, K. Willy, J. Wolfes, S. Sandmann, J. Varghese, and L. Eckardt, "Machine learning in the detection and management of atrial fibrillation," *Clinical Research in Cardiology*, vol. 111, no. 9, pp. 1010–1017, 2022.

[16] L. Chen, Z. Han, J. Wang, and C. Yang, "The emerging roles of machine learning in cardiovascular diseases: A narrative review," *Annals of Translational Medicine*, vol. 10, no. 10, 2022.

[17] H. Hamil, Z. Zidelmal, M. S. Azzaz, S. Sakhi, R. Kaibou, and D. Ould Abdeslam, "Af episodes recognition using optimized time-frequency features and cost-sensitive svm," *Physical and Engineering Sciences in Medicine*, vol. 44, no. 3, pp. 613–624, 2021.

[18] E. Ramaraj *et al.*, "A novel deep learning based gated recurrent unit with extreme learning machine for electrocardiogram (ecg) signal recognition," *Biomedical Signal Processing and Control*, vol. 68, p. 102779, 2021.

[19] A. Çınar and S. A. Tuncer, "Classification of normal sinus rhythm, abnormal arrhythmia and congestive heart failure ecg signals using lstm and hybrid cnn-svm deep neural networks," *Computer methods in biomechanics and biomedical engineering*, vol. 24, no. 2, pp. 203–214, 2021.

[20] W. Lu, J. Jiang, L. Ma, H. Chen, H. Wu, M. Gong, X. Jiang, and M. Fan, "An arrhythmia classification algorithm using c-lstm in physiological parameters monitoring system under internet of health things environment," *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–11, 2021.

[21] O. M. A. Ali, S. W. Kareem, and A. S. Mohammed, "Evaluation of electrocardiogram signals classification

using cnn, svm, and lstm algorithm: A review," in *2022 8th International Engineering Conference on Sustainable Technology and Development (IEC)*, pp. 185–191, IEEE, 2022.

[22] A. Nainwal, Y. Kumar, and B. Jha, "An ecg classification using dnn classifier with modified pigeon inspired optimizer," *Multimedia Tools and Applications*, vol. 81, no. 7, pp. 9131–9150, 2022.

[23] S. Nurmaini, B. Tutuko, M. N. Rachmatullah, A. Darmawahyuni, and F. Masdung, "Machine learning techniques with low-dimensional feature extraction for improving the generalizability of cardiac arrhythmia," *IAENG International Journal of Computer Science*, vol. 48, no. 2, pp. 369–378, 2021.