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Outperforming Optimised Neural Networks for Cardiac Disease Detection

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Abstract: Nowadays, cardiovascular diseases are common, and according to WHO, more than 17.9 million casualties per year are caused due to these diseases. It is vital to both the patient and physician to detect, analyse and treat before too late. The vast advancement in machine learning technology has made a path for identifying and classifying the potential abnormalities in a patient's heart within no time using Electrocardiogram (ECG) signals, enables the physician to treat effectively and, in turn reduces the mortality rate. The accuracy of the existing machine learning (ML) models largely depends on the hyperparameters. Present research work successfully developed an Optimised ML model (OML) with Genetic Algorithm, and Particle Swam Optimization to identify and classify the abnormalities. This trained OML model shared over the IoT device helps in the early prediction of diseases by the patient as well as the hospital management system and helps the doctors to take up the necessary treatment. The results shows that OML models outperforms over the existing Non optimized ML models (NOML) in terms of various performance metrices.

Keywords: *Cardiovascular Diseases, Electrocardiogram (ECG), Internet of Things (IoT), Machine Learning (ML), Genetic Algorithm (GA), Optimised ML model (OML), and Particle Swam Optimization (PSO).*

1. Introduction

Heart disease is a global health issue, and it is responsible for a large number of fatalities worldwide. Early and accurate discovery of heart disease is essential for successfully preventing and treating potentially fatal outcomes. In general, conventional methods of heart disease detection typically involve a combination of patient history assessment, physical examinations, electrocardiograms (ECGs), stress tests, and imaging techniques like echocardiography or cardiac catheterization. These methods have been valuable in identifying potential risk factors, abnormalities, and structural anomalies in the heart [7]. However, they often require extensive human expertise and are subject to interpretation biases, leading to diagnostic errors or delays.

However, recent improvements in Artificial Intelligence (AI) and ML techniques have opened new possibilities for improving heart disease detection and diagnosis in the field of cardiovascular healthcare. Through employing large datasets, AI algorithms can learn patterns and relationships within vast amounts of medical information, enabling them to analyse data with speed, precision, and consistency beyond human capabilities [6]. This transformative technology potentially enhances accuracy, efficiency, and accessibility.

Traditional ANNs consist of a mesh of layers with nodes as neurons, which processes and transmits information. They were trained using backpropagation algorithms, which adjust the connection weights such that the error between the forecast and real outputs is minimized. However, the current study was focused on improving the architecture and training algorithms of ANNs to achieve even higher accuracy and efficiency [14]. Optimized ANN Structure/ML (OML) are utilized in this research for improving the accuracy and efficacy of the system by choosing the Optimal values for the hyper parameters viz., number of hidden layers and number of neurons in each hidden layer.

One area of optimization is the utilization of Deep-Learning (DL) techniques, such as Deep Neural Networks (DNNs) or Convolutional Neural Networks (CNNs), which boast demonstrated remarkable performance in medical diagnostics. These deep learning models allow ANNs to learn complex data, enabling the extraction of intricate features relevant to heart disease detection [1]. Additionally, regularization techniques help reduce the risk of overfitting by adding constraints to the network architecture or adjusting the learning process [2]. But in the literature, it is exposed that contradictory noises are believed to make DNNs susceptible [5].

Further, the integration of optimization algorithms enhances the training process and overcomes challenges like local optima or slow convergence. Evolutionary algorithms, GA and PSO are the methods employed to fine-tune the hyperparameters of ANNs. These algorithms offer efficient ways to search for the optimal configuration of ANNs, leading to improved performance in heart disease detection

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[3]. Optimized ANNs with selected features have demonstrated enhanced accuracy and interpretability in heart disease detection [4].

The continual advancement of ANNs in heart disease detection is evident in the latest research. Studies have focused on fine-tuning network architectures, exploring novel training algorithms, optimizing hyperparameters, and integrating innovative optimization techniques. These advancements aim to improve the robustness, accuracy, and efficiency of ANNs, ultimately enhancing their role in aiding healthcare professionals in diagnosing heart disease.

AI and healthcare professionals can benefit from improved risk assessment, early detection, and personalized treatment plans. The collaborative efforts of medical professionals and AI systems hold great promise for a future where heart disease detection and prevention are more effective than ever before.

This paper is structured as Section I Importance of the work and review of advancement of the technologies used in detection and diagnosis of cardiovascular diseases. Section II Database, Types of Heart Diseases and Methodology adapted for disease classification. Section III Showcase Comparative Analysis of the Existing and Proposed Methods and Discussion. Section IV presents the Conclusion of this research work.

2. Database, Types of Heart Diseases and Methodology

There are several ways to record an ECG, each with its own purpose and level of complexity.

2.1. Common methods for recording ECGs

1) Standard 12-Lead ECG: This is the utmost common method opted in clinical settings. To record the electrical activities of the heart, 10 electrodes are placed at specific points on the patient's body. from 12 different views. These views provide a comprehensive assessment of the heart's function and are used for diagnosing various cardiac conditions.

2) 3-Lead or 5-Lead ECG: These methods use fewer electrodes compared to the standard 12-Lead ECG. They are often used for continuous monitoring in hospital settings, during surgeries, or in emergency situations.

3) Holter Monitor: 24 to 48-hour ECG signal recorded using this device. The patient wears the device during their daily activities, providing a continuous recording that can reveal irregular heart rhythms and transient arrhythmias.

4) Event Monitor: Similar to a Holter monitor, an event monitor is used for longer-term monitoring, typically worn for weeks or months. It's activated by the patient when they experience symptoms, allowing for targeted recording during specific events.

5) Telemetry Monitoring: In hospitals, telemetry units monitor patients' ECGs continuously. Wireless sensors attached to the patient transmit ECG data to a central monitoring station, allowing healthcare providers to monitor multiple patients' heart rhythms simultaneously.

6) Exercise Stress Test: ECG is continuously recorded when the patient exercises on a stationary bike or treadmill. This helps assess the heart's response to physical exertion and detect exercise-induced abnormalities.

7) Ambulatory ECG Monitoring: Devices like patches or wearable ECG monitors can be worn for extended periods, recording the heart's activity as the person goes about their daily routine.

8) Mobile Health Apps: With the advancement of IoT, smartphone apps and portable ECG devices are available for personal use. These devices can record ECGs and provide insights into heart health, but they may not be as accurate as clinical-grade equipment [9].

In our research work, the MIT-BIH Arrhythmia Dataset, which consists of a diverse collection of ECG recordings acquired from patients with different arrhythmias and heart conditions. It consists of 30 minutes of dual-channel ECG signals from 47 individual subjects with 48 records. Most records provide ECG leads II and V1, enabling the analysis of multiple cardiac perspectives.

2.2. ECG Waveform Generation

The Sino-Atrial (SA) Node, which is found in the right atrium and functions as heart's pacemaker, is where the ECG begins. Atrial contraction brought on by the electrical signals forces blood into the ventricles. The P wave is the sequence that the ECG records. The ventricles then contract and pump blood to the rest of the body as a result of the signal that travels from the atria across them. The QRS Complex is what is listed for this. The T wave is the result of the ventricles relaxing at the end.

P wave: the sequential activation (depolarization) of the right and left atria

QRS complex: right and left ventricular depolarization (normally the ventricles are activated simultaneously)

T wave: ventricular repolarization

An arrhythmia refers to an abnormal heart rhythm detected on an ECG. It can occur due to various reasons, such as electrical conduction system instability in the heart, electrical signals irregular firing, or disruptions in the heart's natural pacemaker.

2.3. Common Characteristics of Arrhythmias

1) Sinus Arrhythmia: Irregular rhythm originating from the sinus node (SN), often caused by normal physiological

variations.

2) Sinus Bradycardia: Slow heart rate (<60 beats/minute) originating from the SN.

3) Sinus Tachycardia: Fast heart rate (>100 beats/minute) originating from the SN.

4) Atrial Fibrillation: Rapid and abnormal atrial electrical activity, resulting in irregular ventricular response.

5) Atrial Flutter: Rapid but regular atrial rhythm with characteristic sawtooth pattern.

6) Premature Ventricular Contractions(PVCs): Initial, irregular ventricular beats originating from ectopic foci.

7) Ventricular Tachycardia: Fast, regular or irregular ventricular rhythm, often associated with significant symptoms and potential cardiac compromise.

8) Ventricular Fibrillation: Chaotic, irregular ventricular activity, a life-threatening emergency requiring immediate intervention (defibrillation).

9) Supraventricular Tachycardia (SVT): SVT refers to rapid heart rates originating above the ventricles, often due to abnormal electrical pathways. It can cause palpitations, dizziness, and other symptoms.

10) Long QT Syndrome: This affects the heart's electrical system, which leads to ECG with long QT interval. It can increase the risk of dangerous arrhythmias.

11) Wolff-Parkinson-White(WPW)-Syndrome: WPW is charact-errized by the presence of an extra electrical path between the atria and ventricles. Heart rate spikes and other arrhythmias may result from this.

12) Atrioventricular Block: This condition involves delays or blocks in the electrical signals between the atria and ventricles, leading to a slower heart rate or even skipped beats.

The common five macro-classes are namely Non-ectopic (NE), Supraventricular ectopic (SE), Ventricular ectopic (VE), Fusion (F), and Unknown (Q). The micro-classes of the ECG signal have been categorized with very little ardour. Hence, it serves as our main motivation to study the micro-classification heartbeats of five types, i.e., Normal (N), Left Bundle Branch Block (L), Right Bundle Branch Block (R), Atrial Premature (A), Premature Ventricular Contraction (V).

Table 1. Arrhythmia Vs Features

Arrhythmia	ECG Features
Atrial-Fibrillation	Absence of P waves, irregular R-R intervals
Bradycardia	Slow heart rate, prolonged P-R interval
Tachycardia	Fast heart rate, narrow or wide QRS complexes
Ventricular Tachycardia	Wide QRS complexes, rapid ventricular rate
Ventricular Fibrillation	Chaotic waveform, absence of QRS complexes
Supraventricular Tachycardia	Rapid heart rate, narrow QRS complexes

Table 2 ECG Micro Classification Characteristics

ECG Characteristic	N	L	R	A	V
QRS Complex Width	Narrow (usually < 0.12 seconds)	Significantly widened (usually > 0.12 seconds)	Slightly widened (usually 0.12 to 0.14 seconds)	Usually normal, but may be widened if the ectopic focus is close to the AV node	Wide and bizarre (usually > 0.12 seconds)
QRS Morphology	Smooth and regular	Broad and slurred with bunny ears pattern	Typically normal in appearance	May vary in morphology	Typically wide and irregular
Major QRS Deflections	Upright (positive) in most leads	Broad R-wave	Typically normal in appearance	Maybe upright, inverted, or absent	Wide and deep QRS complex, often with an inverted T-wave
P-Wave Presence	Before each QRS complex			Abnormal P-wave preceding the QRS	Absent before PVC

2.3.1. Normal (N): ECG rhythm exhibits a narrow QRS complex, smooth and regular QRS morphology, upright significant QRS deflections in most leads, and the presence of P-waves before each QRS complex. A normal ECG rhythm indicates a healthy functioning heart with consistent electrical activity.

2.3.2. Left Bundle-Branch-Block (L): It is characterized by significantly widened QRS complexes with a broad and slurred appearance, often resembling bunny ears. Major QRS deflections, especially broad R-waves, while leads V1 and V2 show broad S-waves. LBBB can be associated with underlying heart conditions that affect the electrical conduction in the left bundle branch.

2.3.3. Right Bundle Branch Block (R): It features slightly widened QRS complexes with a characteristic morphology that is typically normal. In R, the QRS complex in leads V1 and V2 shows a broad R-wave, while the significant QRS deflections in other leads remain primarily normal. RBBB can occur in healthy individuals or be related to certain heart conditions.

2.3.4. Atrial Premature Beat (A): A is marked by an abnormal P-wave preceding the QRS complex. The P wave may seem differently from usual P-waves in the ECG, indicating that the heartbeat originates from an ectopic focus in the atria. As are generally benign, but their presence can sometimes suggest an underlying heart issue or trigger.

2.3.5. Premature Ventricular Contraction (V): P is characterized by a wide and bizarre QRS complex that occurs earlier than expected in the cardiac cycle. The QRS complex often features an inverted T-wave. PVCs can occur due to various reasons and may indicate different heart conditions. While isolated PVCs are usually benign, frequent or complex PVC patterns may warrant further evaluation.

The Micro Classification is tabulated for a simple understanding in Table 2.

2.4 Conventional Diagnosis and Management of Heart Diseases

2.4.1. ECG: Essential for diagnosing and classifying arrhythmias. Continuous monitoring (Holter monitor) may be necessary for capturing intermittent arrhythmias.

2.4.2. Medical History and Physical Examination: Important for identifying underlying causes or risk factors.

2.4.3. Treatment Options: Vary depending on the specific arrhythmia, its severity, and associated symptoms. Options include medication, lifestyle modifications, catheter ablation, pacemaker implantation, or cardioversion.

Out of all these, the experience of the specialist in predicting heart diseases from the ECG plays a vital role in reducing the significant risk. This paper helps the specialist to analyze the ECG waveform effectively and easily.

The ECG Signal are contaminated by different interferences leading to the distorted ECG and is difficult for diagnosis, Hence a pre-processing is required to eliminate these patter distortions that helps in improved detection [11]. This is shown in the figure 1 and the pre-processed signal in the figure 2.

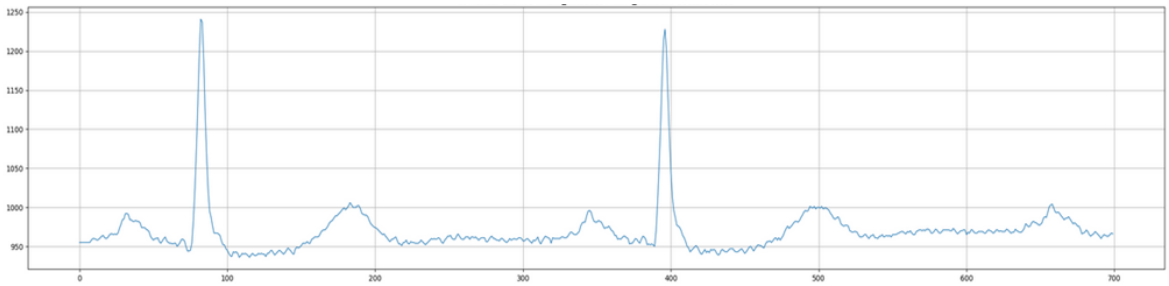

Fig 1. Sample Waveform

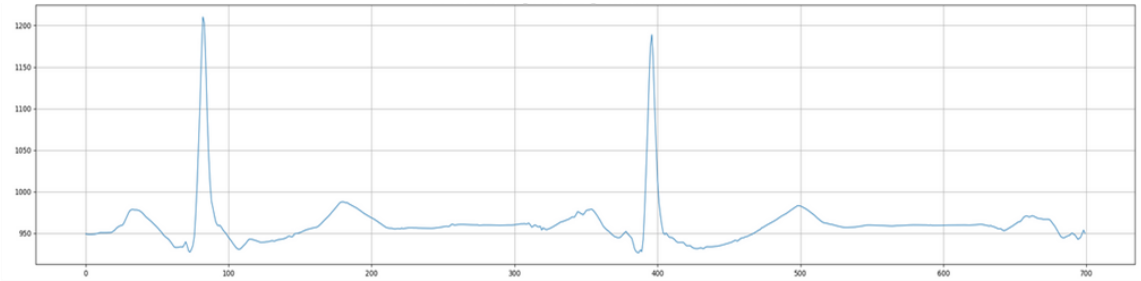

Fig 2. After the Pre-processing

2.5 Conventional Diagnosis and Management of Heart Diseases

The following subsections details each steps followed in the proposed method as shown in the figure 3.

2.5.1 Pre-processing-wavelets

Data Preprocessing: This paper routine thorough data preprocessing steps, including denoising using discrete wavelet transforms (DWT) and z-score normalization of the input dataset. This preprocessing can contribute to improving the model's capability to capture meaningful patterns from the ECG signals and reduces the impact of the noise peaks in the ECG waveforms [12][13] as shown in the fig 2 that may cause deterioration of the accuracy in the classification of ECG defects.

2.5.2 Class Distribution Balancing

A common challenge in medical datasets is the imbalance in defect classes, which may cause under and overfitting of the neural network structure for different categories of defects. To minimize this effect and improve the model performance, in This paper, defect classes are rebalanced using down-sampling and up-sampling techniques that effectively contribute to handling class imbalance.

2.5.3 Training and Testing

Training and testing of an MIT-BIH Arrhythmia Dataset involves using a machine learning model to learn from a subset of the data (training set) and then evaluating its performance on another subset (testing set). This process is crucial for developing accurate arrhythmia detection algorithms. The objective of this phase is to detect patterns, features, and relationships within the data that can help the model distinguish between different arrhythmia classes.

2.5.4 Optimization Algorithms and their application

The evolutionary algorithms such as GA and PSO are widely used in many application to obtain the optimal value of fitness function [10] [14] have proposed optimized neural network for leather defect classification problem. With their methodology, the authors shown that the Optimized networks out performs the existing state

of art methods in the defect detection. It is also shown that the deep learning methods used for defect identification needs complex structure, high amount of data for training and accurate defining of the hyperparameters and network structure can only yield to the high-performance matrices. In our proposed system, a optimized ANN structure is designed and implemented to classify the ECG defects. The configuration of GA with ANN and PSO with ANN is discussed as follows and the obtained results are compared with CNN deep learning algorithm in terms of performance metrices.

Proceeding with the proposed methods, dataset samples are passed through preprocessing module and divided into train and test data with 80% and 20% ratio respectively. The train data is further passed through Class Distribution Balancing module. Advantages of these two steps is discussed in the previous sections.

Now, the train data is further divided into validation train data and validation test data in the same ratio. Now the hyperparameters namely number of layers in between input and output (NLIO) layers and total neurons in each layer (TNL) of the neural network structure are obtained through optimization techniques such as GA and PSO.

2.5.5 N Steps for Optimized ANN using GA

N1. Define the initial variables for the GA i.e Range of values for variables as NLIO =[1, 10], TNL = [5, 50], selection-probability sp=0.5, crossover-probability cp=0.8, mutate rate r=0.2, and total population size =[100], total iterations Ti=50. Iteration I=1.

N2: Compute the fitness function (accuracy Ac)

N3: Perform mating pool selection based on sp

N4: Compute crossover based on cp

N5: Perform Mutation based on r

N6:Sort the population based on fitness

N7: if I<= Ti, compute from N3 else save OANN hyperparameters and terminate.

2.5.6 N Steps for Optimized ANN using PSO

N1: Define initial the variables for PSO i.e, randomly initialize hyperparameters as NLIO =[1, 10], TNL = [5, 50], Ti= 150, a1, a2 random numbers in [0 1], Total particles TP =20, constriction factor (C) social and cognitive parameters as c1=1.5, c2=1.5 and C=1.

N2: These parameters are initialized within specified variable intervals using the formula

Va(i) = Va(i) * (Vahighlt(i) - Valowlt(i)) + Valowlt(i)

N3: Velocity Initialization: Calculate initial velocities for each Va. For the lower interval boundary velowlt(i), use -1 * (Vahighlt(i) - Valowlt(i)),

and for the upper interval boundary vehighlt(i), use Vahighlt - Valowlt.

N4: Calculate the velocity within the interval using

veInt(i) = ve(i) * (velhighlt(i) - vellowlt(i)) + vellowlt(i)

for each variable.

N5: Initial Fitness Evaluation: Calculate the fitness function Ac for each individual in the population.

N6: Treat these fitness values as local minima for each variable. Identify the minimum fitness value and consider it as the initial global minimum. Designate this individual as

the best population member in the initial population.

N7: Iterations. Calculate the inertia weight w as (Ti - I) / Ti. Update the velocity using the equation

ve(i) = C * (w * ve(i) + c1 * r1 * (localva(i) - va(i)) + c2 * r2 * (globalva - va(i))).

N8: Update the position of each variable using

va(i) = va(i) + ve(i).

N9: Calculate the fitness-function for the updated position. Update the best local positions (localva(i)) [8] if the fitness is improved compared to the previous fitness. Update the globalva(i) with the variable values that resulted in the minimum fitness function. N7 is repeated until the maximum iteration is reached.

The obtained optimum OANN Structures using OANN-GA and OANN-PSO are validated using the validation data the structure is evaluated to obtain the maximum OANN validation accuracy. Final step gives the optimal OANN Structural parameters. The optimal network is verified using the test data and the results are compared with the CNN methodology. The next session discusses the performance metrics of proposed algorithms.

3. Existing/Proposed Method Results and Discussion - A Comparative Analysis

Initially, the dataset samples are partitioned into two distinct subsets: the training data and the test data. This division is carried out in a manner that allocates 80% of the samples to the training set, ensuring that a substantial portion of the data is available for training the model. The remaining 20% of the samples form the test set, which is reserved for assessing the model's performance and generalization capabilities.

Table 3 Pre-Processed Data

Class	Total	After Pre-Processing (Up sampling)
N	75011	5000
L	8071	5000
R	7255	5000
A	2546	5000
V	7129	5000

The results of the pre-processing are displayed in Table 3. Where the total column shows the actual number of samples with in each defect class and the Up Sampled data.

The Table 4 shows classification performance of proposed OANN-GA with respective each defect class.

Table 4 The classification performance of the proposed OANN-GA

Class	Sensitivity	Specificity	Accuracy	Accuracy
N	0.9690	0.9941	0.9891	98.72
L	0.9980	0.9991	0.9989	
R	0.9975	0.9940	0.9984	
A	0.9728	0.9924	0.9896	
V	0.9968	1.0000	0.9994	

The Table 5 shows classification performance of proposed OANN-PSO with respective each defect class.

Table 5 The classification performance of the proposed OANN-PSO

Class	Sensitivity	Specificity	Accuracy	Accuracy
N	0.9984	0.9984	0.9996	99.92
L	1.0000	0.9998	0.9998	
R	1.0000	0.9996	0.9996	
A	0.9988	0.9999	0.9996	
V	0.9988	1.0000	0.9998	

The following are the Confusion Matrix obtained with the proposed methodologies.

		Predicted				
		N	**L**	**R**	**A**	**V**
Actual	**N**	4845	14	6	135	0
	L	7	4990	0	3	0
	R	15	1	4970	14	0
	A	92	3	14	4891	0
	V	4	0	12	0	4984

Confusion Matrix of proposed OANN-GA

		Predicted				
		N	**L**	**R**	**A**	**V**
Actual	**N**	4992	2	3	3	0
	L	0	5000	0	0	0
	R	0	0	5000	0	0
	A	3	0	3	4994	0
	V	0	3	3	0	4994

Confusion Matrix of proposed OANN-PSO

The figure 4a, 4b, 4c shows the obtained optimized OANN-PSO Structure and its parameters. These parameters show that the obtained structure is lot more simpler compared to the existing complex CNN Networks used for the classification.

From the figures 5-7 it is observed that the proposed OANN-PSO and OANN-GA outperform the existing state of art methods for cardiac disease detection. Among the proposed methods the OANN-PSO outperforms the OANN-GA with an accuracy of 99.92%. The metrices are outlined in the Table 6.

```
Layer (type)                 Output Shape              Param #
=================================================================
dense_8062 (Dense)           (None, 49)                17689

dense_8063 (Dense)           (None, 49)                2450

dense_8064 (Dense)           (None, 49)                2450

dense_8065 (Dense)           (None, 5)                 250

=================================================================
Total params: 22,839
Trainable params: 22,839
Non-trainable params: 0
```

Fig. 4a Optimized OANN-PSO - Network Structure

```
Number of Hidden Layers: 3
Number of Neurons in Each Hidden Layer: 49
```

Fig. 4b Optimized OANN-PSO - Layer Parameters

```
Other Important Parameters:
Number of Particles in PSO: 20
PSO Lower Bounds (Num Hidden Layers, Num Neurons): [1, 5]
PSO Upper Bounds (Num Hidden Layers, Num Neurons): [4, 50]
```

Fig. 4c Optimized OANN-PSO - Other Network Parameters

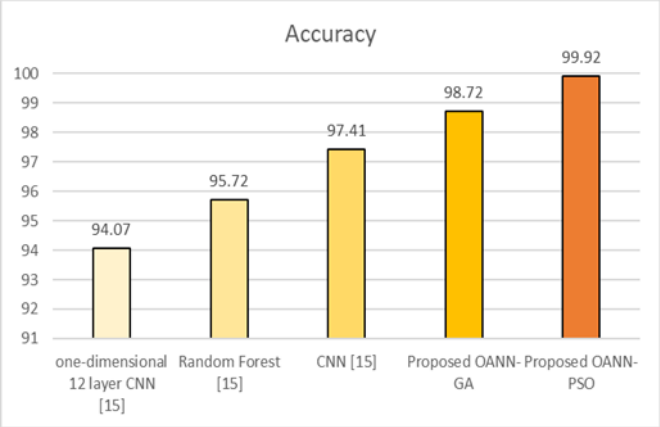

Fig. 5 Over all accuracy of the proposed OANNs structures

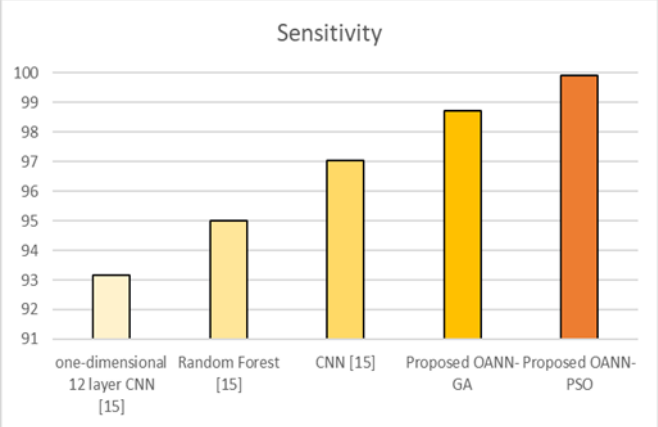

Fig. 6 Over all sensitivity of the proposed OANNs structures

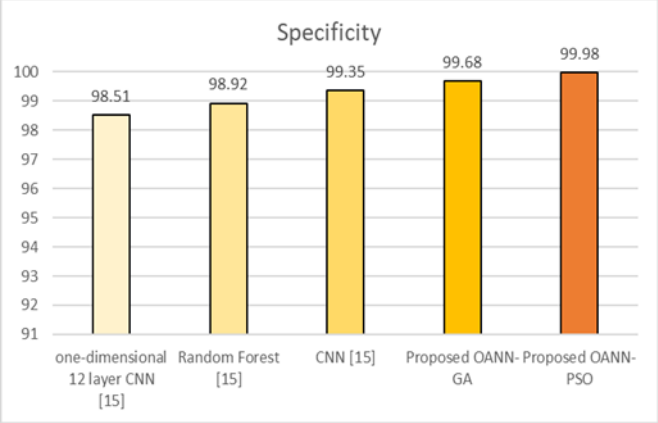

Fig. 7 Over all Specificity of the proposed OANNs structures

Table 6 Over all Performance matrix and the network structure

Methodologies	Accuracy	Sensitivity	Specificity
One-dimensional 12 layer CNN [15]	94.07	93.17	98.51
Random Forest [15]	95.72	95.01	98.92
CNN [15]	97.41	97.05	99.35
Proposed OANN-GA	98.72	98.72	99.68
Proposed OANN-PSO	99.92	99.92	99.98

After obtaining initial results using this split and evaluating the model's accuracy, a subsequent step is introduced. An additional 20% of the dataset, distinct from the previous test set, is considered. This 20% portion is now incorporated into the training set, augmenting its size and diversity. The model is then re-evaluated using this expanded training set.

Remarkably, even with the introduction of this new data and the enlargement of the training set, the model manages to achieve the same level of accuracy as before. This outcome underscores the model's robustness and generalization capabilities, implying that the performance achieved initially was not solely reliant on the specific composition of the original training and test sets. The model's ability to maintain its accuracy despite changes in the dataset distribution suggests its potential to handle varying and previously unseen data effectively

4. Conclusion

In the modern world, cardiovascular disease is becoming a serious health issue. The ECG is crucial for making an early diagnosis of the heart condition. Unfortunately, expert-level medical resources are hard to come by, and it can be difficult and time-consuming to recognize the ECG signal visually. In contrast to the existing literature, which primarily categorizes the five main categories of MIT-BIH Arrhythmia database are NE, SE, VE, F, and Q, our study mainly focuses on specific micro-classes, including N, L, R, A, and V. The proposed work OANN-GA and the OANN-PSO has yielded a relatively higher accuracy. The Proposed OANN-PSO has an Top-notch performance in the overall classification of micro-classes of dataset with Accuracy 99.92, Sensitivity of 99.92, and Specificity of 99.98.

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