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Patient Heart Disease Prediction using Convolutional Neural Network with IoT Node

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ABSTRACT

Arrhythmia is one among the leading cardiovascular disease (CVDs), which is responsible for sudden loss of life among the cardiac patients. In the past few years, a tremendous growth in the discipline of IoT is witnessed, which contributes a lot in the healthcare system as it enables continuous monitoring of the patients yet there is a need for an advanced automatic monitoring system for the classification of cardiac arrhythmia. The traditional methods experience a great deal of disadvantages in terms of the classification accuracy, which is addressed through proposing an optimized deep convolutional neural network (Deep CNN) for IoT cardiac arrhythmia classification. The proposed technique assure ceaseless healthcare monitoring of a patient as it employs the IoT networks to collect the Electrocardiograph (ECG) signal, which is considered as a significant modality for arrhythmia classification. The proposed optimized deep CNN is developed through the consolidation of the rider optimization algorithm (ROA) in the deep CNN classifier for tuning the hyper-parameters. The proposed model is evaluated with MIT–BIH dataset and the outcomes are analysed with the existing methods in order to reveal the efficacy of the proposed optimized deep CNN technique. The exploration of the classification methods based on accuracy, sensitivity and specificity reveals that the proposed method acquires an effective specificity with 98.8%, accuracy with 98.7% and sensitivity with 98.9%

Keywords: Arrhythmia classification, IoT networks, ECG signal, Deep learning classifier, Optimization

1. INTRODUCTION

Human heart, indispensable part of circulatory system transports the oxygenated blood to other segments of the human body and extracts the contaminated blood, which is combined with carbon dioxide from the human body. The Sinoatrial node, also known as natural pacemaker is located in the right atrium of the human heart and it is responsible for the formation of electric impulse. The heart beat was controlled through that electric impulse hence, it is known as Rhythm. Change in electric activities of Rhythm with respect to the time is recorded in the graph Known as Electrocardiograph ECG. The acquired ECG signals help the physician in diagnosing the state of heart [6]. In general an ECG is referred as the waveform encompassed in PQRST pattern, which comprises of pinnacles and depressions. Sinus rhythm is recognised as one sequence of the waveform pattern that resembles regular cardiac rhythm. The intervals, such as PR, QT, QR Complex, RR and the magnitudes of QRS complex waves, P wave, T wave and S waves are considered as the prime measures to determine the heart conditions. The deviation from the normal value in the measurements indicates the abnormal rhythm known as Arrhythmia [1]-[6].Cardiac arrhythmia is defined as the abnormal heartbeats, which may be responsible for the unexpected life loss of a victim [8] [2]. Hence, the continuous monitoring concerned with the cardiac behaviour of patients is required to avoid unexpected life loss and also provide on-time medical support. In such case, the smart health care plays a significant role as it enables continuous monitoring of cardiac behaviour and to render timely medical support [5].

Smart health care systems are described as the assortment of sensors, services, clinical devices, and some applications that can interface and communicate between each other with the assistance of internet [9][10]. The aforementioned framework is established to handle the increasing demand of health-care services and system [11][12].The advancement in smart health care system offers a real-time and accurate diagnosis of the cardiac diseases, which is the great threaten to the human life [13] [14][15]. The role of Internet of things (IoT) in the progressive health-care system is remarkable as it facilitates the real-time monitoring system. Observation and admittance to clinical consideration with significant reduction in the monitoring cost, prevention and prior diagnosis are considered as the prime steps in medical health. IoT networks are responsible for the accumulation of ECG signals from the victim and permits the feature extraction through the Machine learning techniques. The advancement techniques employed in the deep learning method facilitates the automatic detection of arrhythmia [5].

Recent few years witness the development of various classification and feature extraction process that are widely used for precise detection of cardiac arrhythmias. The features, such as VF filter leakage measures (VFF) complexity measure (CPLX), auto correlation function (ACF) and threshold crossing intervals (TCI) combined with classifiers based on machine learning are currently utilised for Automatic diagnosis of arrhythmia through ECG signals. The concept is utilised for the feature extraction based on phase space representation (PSR), spectral algorithm (SPEC) and wavelet transforms [15]. Various researchers deploy their efforts to provide best solutions for the automated classification of cardiac pulse rate. The existing methods are mainly classified into two types they are the methods based on deep learning techniques and methods based on the feature engineering techniques. Though the most of the existing method in feature engineering attains a significant growth in medical-care, there exists inconvenience in selecting the self-sufficient classifiers and utilizing the feature- set for the classification of heart beats . Therefore, it may cause immense effect in the recognition of controversial heart beats. The deep learning techniques are restricted as it explores the unitary impression only from the unprocessed ECG signals. The RR intervals and the frequency patterns are not exploited for the classification purpose. In addition, to provide the adequate data for priming and executing the profound neural networks, numerous research projects followed a one-sided assessment strategy, in which they incorporated heartbeat samples from the entire dataset and afterward haphazardly dissect all cardiac pulses for authentication, model training and evaluation. The cardiac pulses from the same victim probably going to show-up in both the test datasets and training datasets prompting an over assessment in model presentations furthermore more the over optimistic result conceal the restriction of the neural networks [1]. Various classification algorithms especially, Random Forest, K-nearest neighbour and support Vector Machines along with hand engineered features are employed in the traditional methods. In addition, various researches made an attempt to utilise neural networks for cardiac arrhythmia determination. Due to the advancement in the field of deep learning, many researchers strive to handle the issues in the determination of cardiac arrhythmia utilizing the Convolution neural network, which is the predominant branch of deep learning domain [3].

This research concentrates to develop an adaptive technique for automatic arrhythmia classification from the ECG signal of the victim through the optimized deep convolutional neural networks. The ECG signal gathered from the patients is reciprocated to the Sink nodes in the IoT network, where the signals are analyzed for the classification of the arrhythmia using the proposed ROA-based deep convolutional network. The contribution of the research is given below:

- Proposed ROA-based deep CNN method provides a ceaseless and completely automatic monitoring of arrhythmia suspected victim, which enables the real-time support from the physician.
- ROA-based deep CNN method enables the early prediction of arrhythmia, avoiding the hazardous situation as it renders the on-time medical support.
- The extraction of feature and the reduction of dimension are the important steps to reduce the latency that are occurred due to the training process in the classifier and such intermediate processing steps are executed within the ROA-based deep learning CNN, which minimizes the execution time.
- The experimental analysis of the proposed ROA-based deep CNN methods with respect to the existing methods is enabled to prove the supremacy of the developed classification model.

2. RELATED WORKS

The review of the existing literature is discussed as follows: Jinyuan He, *et al.* [1] developed a dynamic heart beat classification method with adjacent features and multichannel heart beat convolution neural networks (MCHNN).The prime advantage of the method is that it utilized both the temporal and the frequency pattern from the heart in order to obtain effective classification hence, it achieve the accuracy of about 91.4%. The drawback of the method is that the heart beat rhythms are not integrated well to the networks. Additionally, this method can be easily affected through other learned features. Rajendran Sree Ranjani [2] designed a wearable sensor equipped with IoT and machine learning techniques for constant monitoring of victim, who is suspected to have arrhythmia. The advantages of IoT and machine learning techniques was that it offers the continuous monitoring and recordings for the prolonged period thereby, preventing the severity of arrhythmia. However, the prior detection and accurate determination of arrhythmia patients mainly depend on additional parameters regardless of ECG. Adeleh Bitarafan *et al.* [3] developed a scheme, which is based on deep learning techniques using the long short term memory (LSTM) and dilated convolution layers for arrhythmia classification. The LSTM technique permits modelling the relation among different cardiac pulses in sequence and has indestructible prospects to be applied in real-world applications as it does not require the expert knowledge. The main disadvantage of the LSTM method is that we could carry out the experiments only under the weighted cross entropy loss. Anoop Vylala & Bipin Plakkottu Radhakrishnan [4] developed an algorithm known as Taylor-SCA algorithm, which is developed with the integration of both Taylor series algorithm and sine cosine Algorithm. The time-based features and the frequency-based features utilized in Taylor-SCA algorithm enhance robustness along with accuracy of the classification. The Taylor –SCA algorithm shows an imperative output with the accuracy of 95.45%.The main drawback is that the method lacks fully automated method for detection. Rohan Panda, *et al.* [5] developed an Arrhythmia classification system with the assistance of fixed frequency range empirical wavelet transform and Deep Convolutional Networks. The supremacy of the system is that it enables multi-scale analysis of ECG signals, which enhances the average accuracy level. Yet more episodes are required for training in order to obtain bias, optimal kernel and weight parameter, which is the major challenge of the research. Maheswari Arumugam and Arun Kumar Sangaiah [6] developed a wavelet-based algorithm for arrhythmia classification. The wavelet-based algorithm method is utilized to find out the victim, who was affected by cardiac arrhythmia without any delay and provides instant and proper medical support to them without inducing turmoil and fear in patients without heart ailments. The ideal time frequency resolutions are explored through the ECG signal is considered as the supremacy of the system.. The main drawback is that it requires machine learning and deep learning based solutions for effective classification.

2.1 Problem statement

The major challenges considered for this research of IoT arrhythmia classification is enumerated below:

- Although deep learning methods have made remarkable progress in the health care sector, they still experience immense challenges. The structural characteristics of ECG signals may differs from one individual or (patient) to another, which in turn results in the performance degradation to the existing models when the ECG signals are tested with inter-patient standard model. The inconsistency among the training data and test information, alluded to as space shifts, may disregard the fundamental independent identically distributed (I.I.D) premise in learning-based plans [7]. In order to avoid some kind of drifts, the training of the deep learning methods should be strengthened for which we are developing a new model in this research.
- In [4], the authors presented the Taylor-SCA-based expert detractor neural network, where the training model is deliberated, but there exists limitations regarding the extraction of the texture and temporal features.
- In [6], the necessity for machine learning or a deep learning idea is focussed, where the authors implemented the detection process using the wavelet transform-based algorithm, which suffers a lot from knowledge extraction, training, and classification.

3. SYSTEM MODEL OF IOT NETWORKS

IoT is an innovation, which creates the data exchange between the devices within the certain radio frequency as it assembles various devices, such as sensors, smart phone, and routers via internet without any interruption from human being. The IoT network sensor comprises of three main frameworks they are: main station, cluster heads and Z number of IoT nodes as shown in the figure 1. Let us represent the IoT nodes as H_k. There are Z number of IoT nodes in the IoT network, where the communication range of each node is evenly distributed within a certain frequency range of G_f and G_l. Each and every IoT nodes acquired a unique ID and these nodes are assembled to form clusters within the networks. The cluster group formation initiates the transmission of data from the IoT nodes to their respective cluster heads, which is represented as C_h. Let m be the total number of cluster heads in the network and is denoted as, $(1 \le h \le m)$. Let the distance between IoT nodes and the cluster head is represented as, ∂_{kh}. There is a base station (B_S) in every IoT framework and it is established to receive all the data from the cluster heads. The distance between the cluster head and the base station is represented as ∂_{hs}. One of the main parameter considered while designing the IoT frame is the energy consumption since it is impossible to recharge the IoT nodes. The initial level of energy in the IoT node is considered as E_z. The energy dissipation takes place when the IoT nodes communicate with the cluster heads and to the base station. The energy level is updated for every transmission of data from the IoT nodes to the base station and the dissipation of the energy at the receiver end is determined through the radio electronics. Figure 1 depicts the system model of IoT network.

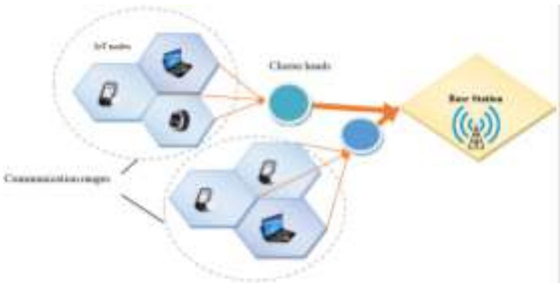


Figure 1. A model for IoT Network

4. PROPOSED MODEL FOR IOT ARRHYTHMIA CLASSIFICATION USING ROA BASED DEEP CNN

This section composed of the proposed model for IoT arrhythmia classification using ROA based deep CNN .The first stage in the proposed framework is the information acquisition stage in which the data from the victim such as, ECG signal is collected through the IoT nodes. These nodes are connected to the base station, which is also known as Sink nodes. The extracted ECG signal from the sink nodes is pre-processed and it is exposed to the Deep Convolutional neural networks. The Rider optimization-based Deep CNN is utilised here for the purpose of extraction of feature, minimizing the dimension and connecting the neurons from one layer to the successive layer to obtain better arrhythmia classification. The proposed IoT Arrhythmia classification using ROA based deep CNN provides the continuous monitoring of the arrhythmia patients hence, it enables the on-time medical advice from the physician. The system model of the proposed model for IoT arrhythmia classification using ROA based deep CNN is illustrated in the figure 1.

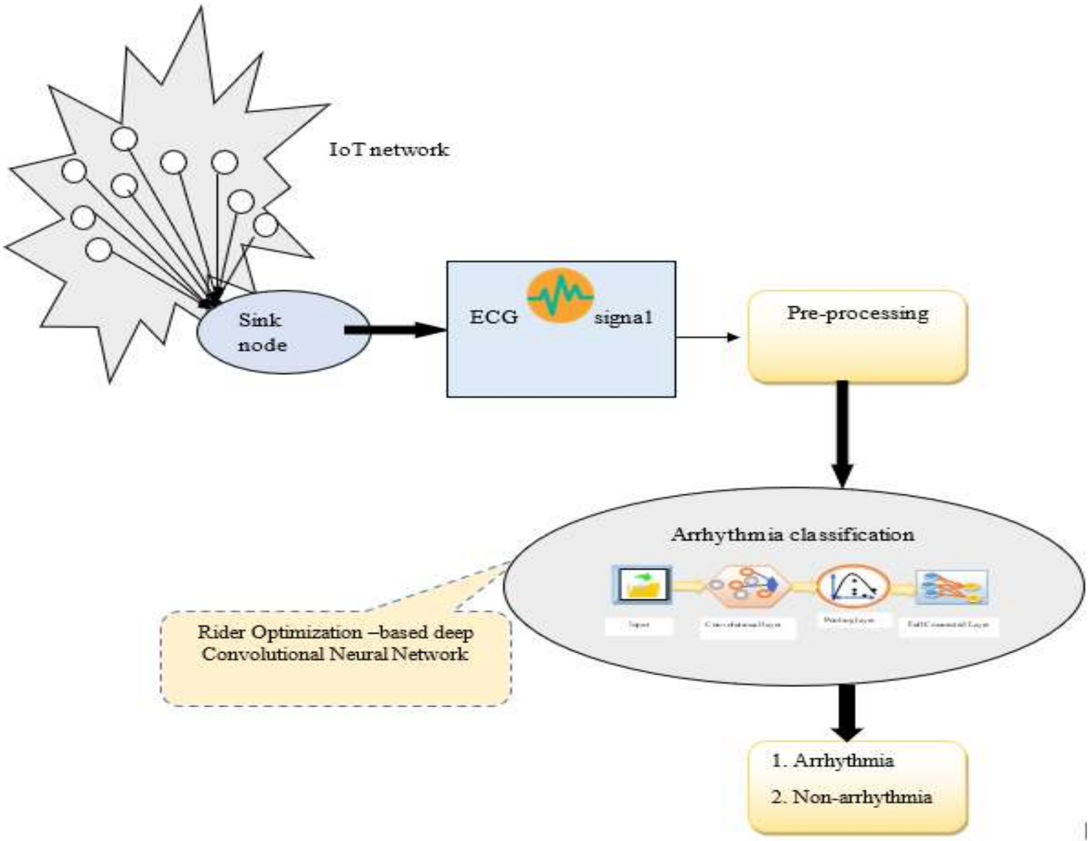


Figure 2. Block diagram of the proposed method of classification

4.1 Pre-processing:

The ECG signals collected at the sink node are subjected to the pre-processing using the StandardScaler Transform, which normalize and standardize the input signal for the processing of the signals for arrhythmia classification. Let the ECG database is denoted as, $\Re = S_i$, where S_i be the i^{th} input signal and let there are N number of signals in the database. The signals are processed in the deep CNN classifier through a set of tuneable weights and the state of the person regarding the arrhythmia and non-arrhythmia is derived. S_i is presented to the classification module, where the Deep CNN classifies the signal as arrhythmia and non-arrhythmia.

4.2 Proposed ROA-based deep CNN for Arrhythmia classification

In this section, the arrhythmia classification done using the proposed ROA-based deep CNN is deliberated. Generally, in IoT-based Arrhythmia classification, the analysis of ECG images are established through the machine learning techniques, which requires a proper feature extraction process for the accurate classification. Hence, the Deep CNN is employed, which effectively extracts the features from the given signals for arrhythmia classification [33] [30]. The training of Deep CNN requires an efficient and well-structured optimization algorithm in order to overcome the issues of data imbalance, accuracy degradation, and computational complexity. The properties of four rider groups encompassed in ROA have the potential to surpass the above-mentioned training issues. Hence, ROA is used in this research for training the hyper-parameters of Deep CNN [32]. The deep CNN is one among the deep learning-based classifiers that train the system to explore their functional frameworks utilizing the collected datasets in order to provide accurate classification results. The Deep CNN architecture comprises of three operational zones, which are enlisted as: (a) the convolutional zone, (b) the pooling zone, and (c) fully connected zone . Figure 3 shows the architecture of Deep CNN.

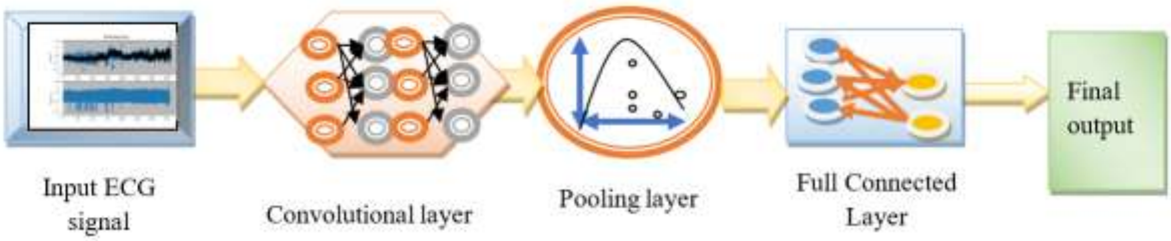


Figure 3. Architecture of Deep CNN

Convolutional Zone: The core layer of deep CNN is the convolutional layer, where the extraction of features is carried-out. The first convolutional layer is responsible for the extraction of lower-grade features, such as edges, colours and the successive layers extract the high-level features. The following equation represents the output of the convolutional network is expressed as,

$$\left(M_\psi^n\right)_{J,Y} = \left(W_\psi^n\right)_{J,Y} + \sum_{q=1}^{Q_1^{u-1}} \sum_{\theta=-I_1^i}^{Q_1^i} \sum_{\lambda=-I_2^i}^{Q_2^i} \left(V_{\psi,q}^i\right) * \left(M_q^{i-1}\right)_{J+\theta,W+\lambda} \tag{1}$$

where, $\left(M_\psi^n\right)_{J,Y}$ represents the feature maps from the convolutional layer in i^{th} position, which is centered at (J, Y). The bias of the layer is represented as, W_ψ^n and $V_{\psi,q}^i$ is the weight between the layers. The parameters, such as λ , θ and q represents the feature maps, which forms the output within the convolutional filters

Max-pooling zone: The pooling layers minimize the dimension of the extracted data by combining a neuron of one layer with the output obtained from the cluster of neurons in the successive layer.

Fully connected zone: Each and every neuron in a layer is connected to the neurons in the other layers in the fully connected layer to obtain a better classification. The general expression of the fully connected layer is given as,

$$F_\psi^n = \eta\left(M_\psi^n\right) = \sum_{q=1}^{Q_1^{u-1}} \sum_{\theta=-I_1^i}^{Q_1^i} \sum_{\lambda=-I_2^i}^{Q_2^i} \left(V_{\psi,q}^i\right) * \left(M_q^{i-1}\right)_{J+\theta,W+\lambda} \tag{2}$$

where, M_ψ^n is the output of the convolutional layer and it is obtained as

4.2.1 Rider optimization for tuning the hyper-parameters of Deep CNN:

The ROA [31] categorized under frictional computing technique, solves the optimization problems through the imaginary ideas and concepts of the riders. The main advantage of ROA with respect to the other nature-inspired and artificial computing methods relies on the maximal global optimal converging tendency and an effective balance in the exploration and exploitation issues. ROA comprises of four categories of riders that target the final destination to become the winner of the race. The four categories of riders are the Bypass rider (P), Follower (R), Overtaker (O) and the Attacker (A).The brief description of each rider are given below:

Bypass rider (P) **:** Let us represent the bypass riders as, P .The Bypass rider is the first category of the rider considered in ROA, which selects the alternative path to reach the destination.

Follower (R)**:** The follower riders adopt the path of the main rider, who is in the leading position to attain the target and this type of follower is represented as R .

Overtaker (O)**:** The overtaker rider adopts his own path with respect to the orientation of the leading rider and the overtaker rider is represented as O .

Attacker (A)**:** The attacker is a violent rider, who utilize his maximum speed to attain its target and this category of rider is represented a A.

I. Algorithmic steps of ROA: The algorithmic structure of ROA along with the mathematical representation is explained in this section. The processes involved in Rider Optimization algorithm are:

Initialization: The first process involved in the ROA is the initialization of rider parameters and their groups, which is given by,

$$X_a = \{X_a(c,d)\}; 1 \le c \le T; 1 \le d \le U \tag{3}$$

where, $X(c,d)$ represents the position of c^{th} rider with respect to d, U is the dimension of number of coordinates, T is the total number of riders, which is the sum of riders in each category and is represented as,

$$T = P + O + R + A \tag{4}$$

Selection of the fittest solution using the success rate: The second process employed in ROA is finding the success rate, which is calculated based on the interval between the target and the position of the rider. The success rate thus obtained is utilized to determine the position of the leading rider. The following equation determines the success rate (α).

$$\alpha = \frac{1}{X_L - X_t} \tag{5}$$

where, X_L represents the orientation of the rider, who is in leading position and X_t is the position of target.

Update in the rider position: The third process adopted in ROA is updating the position of each rider. The position of riders, such as bypass rider, overtaker, attacker and follower should be updated to find the winner. The position of bypass rider is updated through the following equation.

$$X^p_{a+1}(c,d) = \delta[X_a(\tau,d) * \beta(d) + X_a(\gamma,d) * [1-\beta(d)]] \tag{6}$$

where, τ is the random number which ranges from 1 to T, δ represent the random number from 0 to 1, γ is the number, which chooses a random value within R. β is the random number between 0 and 1with the size of $[1 \times U]$. The position of the follower is updated as,

$$X^R_{a+1}(c,r) = X_L(K,r) + [\cos(D^a_{c,r}) * X_L(K,r) * \xi^a_c] \tag{7}$$

where, r represents the coordinate selector, X_L represents the leading rider's position, K represents the leading rider's index, Steering angle of c^{th} rider in the r^{th} coordinate is represented as $D^a_{c,r}$ and ξ^a_c represents the distance covered by the c^{th} rider. The position of overtaker is updated through the given equation as,

$$X^o_{a+1}(c,r) = X_a(c,r) + [g^I_a(c) * X_L(K,r)] \tag{8}$$

where, $X_a(c,r)$ represents c^{th} rider in the r^{th} coordinate. The direction indicator of c^{th} rider with respect to time I is given as, $g^I_a(c)$. The orientation of attacker is given as,

$$X^A_{x+1}(c,d) = X_L(K,d) + [\cos(D^a_{c,r}) * X_L(K,d) * \xi^a_c] \tag{9}$$

where, $X_L(K,d)$ represents the leaders' position, steering angle of c^{th} rider in the r^{th} coordinate is represented as, $D^a_{c,r}$ and ξ^a_c represents the distance covered by the i^{th} rider.

Update the optimization parameters: The ultimate solution is obtained through updating the parameters of the riders. The gear, activity and steering angle counter are required to be updated for all the riders at the end of all the iteration in order to re-evaluate the success rate and determine the optimal solution.

Termination: The above said steps are continued until the determination of leading rider, who is considered as the winner at the end of the race. The output from the optimization is the optimal hyper-parameters for tuning the deep CNN classifier.

5. RESULTS AND DISCUSSION

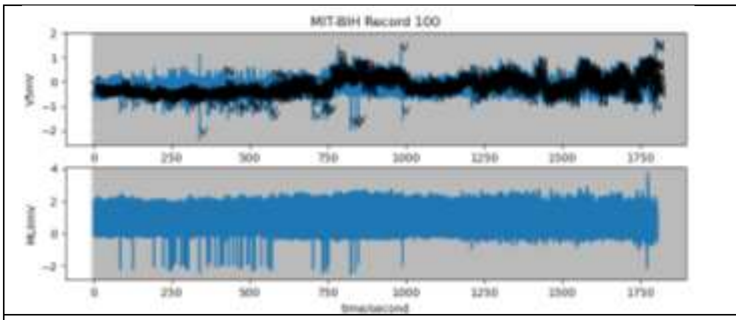
This section explains the result and the discussion of the proposed ROA-based deep CNN and in order to prove the effectiveness of the proposed technique, the comparative analysis is done with various conventional techniques, like LSTM, DCNN, NN and logistic regression.

5.1 Experimental setup

The ROA-based deep CNN for IoT arrhythmia classification is implemented in PYTHON 3.7 that is installed in the PC operating with Windows 10 Operating system and 4GB memory. The implementation is done using the MIT-BIH database [29]. The MIT-BIH Arrhythmia database is a most significant clinical database, which comprises of two days extraction of Two Channel ECG recordings. The data is acquired from 47 persons observed through the BIH Arrhythmia research room within the year range of 1975 to 1979. The twenty three observations were taken from the bunch of 4000 ECG recordings from the complex populace of 60% of inmates and 40% of the outpatients at the Boston's Beth Israel hospital. The remaining records were randomly chosen from the set, which includes more unconventional yet diagnostically remarkable arrhythmias, which is not represented in a small random sample.

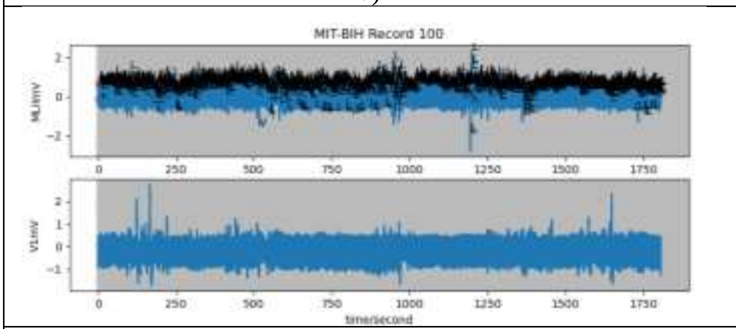
5.2 Experimental results

Figure 4 manifest the obtained ECG signals of the arrhythmia patient, which is transmitted to the physician in any part of the world. This enables the physician to examine and analyse the ECG signal and provide the on-time medical support. The physician analyse the ECG signals and helps to determine whether the patient is affected by arrhythmia or not. Moreover, this analysis provides proper guidance to the patient. Hence, the ROA-based deep CNN for IoT arrhythmia classification provides proper monitoring service, which could protect the patient's life. Figure 4 a) and 4 c) indicates the sample ECG signals, while figure 4 b) and figure 4 d) signifies the communication of the ECG signals with the physician and the patient.



a)

b)



c)

e

d)

Figure 4. Experimental analysis of the proposed ROA-based deep CNN a) sample ECG signal-1, b) Signal communication of signal-1 with the Physician, c) sample ECG signal-2, and d) Signal communication of signal-2 with the Physician

5.3 Execution Parameters

The parameters considered to analyse the performance of this research is accuracy, sensitivity and specificity, which are discussed as follows:

Sensitivity: Sensitivity measures the correctness of the genuine identities and it is described as,

$$\text{Sensitivity}\ (Sen) = \frac{Q}{Q+Z} \tag{10}$$

Accuracy: Accuracy is the closeness of the classification results with that of the ground truth, which is expressed as,

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$$\text{Accuracy } (Acu) = \frac{Q+N}{Q+N+Z+J} \tag{11}$$

Specificity: Specificity refers to the correctly identified negative identities, which is formulated as,

$$\text{Specificity}\,(Spe) = \frac{Q}{Q+J} \tag{12}$$

where Q represents positive value , Z is the false positive value, N is the true negative value and J is the false positive value.

5.4 Competing methods

The conventional methods utilized for the comparative analysis for the ROA-based deep CNN is enlisted as: Long short-term memory (LSTM) [3], DCNN [5], neural network (NN) [36], random forest (RF) [34], and Logistic regression [35].

5.5 Performance analysis of the proposed ROA-based Deep CNN

The analysis of the proposed ROA-based Deep CNN method with respect to the epoch is presented in the figure 5. From the figure 5 a), it is clear that the accuracy of the proposed ROA-based deep CNN technique is increased with increase in the epoch value. The proposed ROA-based deep CNN technique attains 94.4% accuracy when the epoch is 20 at 80% of training. When epoch is 40, the proposed ROA-based Deep CNN acquires 94.7% of accuracy with 80% of training. The highest value of accuracy, 97.8% is achieved when the epoch is 100 and with training 80%. From this figure 5 a), it is evident that the proposed ROA-based deep CNN surmount the other state-of-art technique in terms of accuracy with 80% of training. The figure 5 b) shows the performance analysis of the proposed ROA-based deep CNN techniques in terms of sensitivity with respect to the epoch. From the figure 5 b, it is clear that there is a hike in sensitivity with respect to the increase in epoch value. It achieves 94.7% of sensitivity when the epoch is 20. At the maximum epoch of 100, the proposed ROA-based Deep CNN attains the best sensitivity range of 97.8%. Figure 5 c) represents the performance analysis of proposed ROA-based deep CNN method in terms of specificity with respect to epoch. The figure 5 shows that the proposed ROA-based deep CNN achieves 95% of sensitivity when the epoch is 60 and for 50% of training. The maximum value of specificity of the proposed ROA-based deep CNN is noted as 97.9%, which exceeds the other techniques employed for the comparison. From the above discussion, it is clear that the ROA-based deep CNN technique outshines the other techniques in terms of specificity, sensitivity, and accuracy.

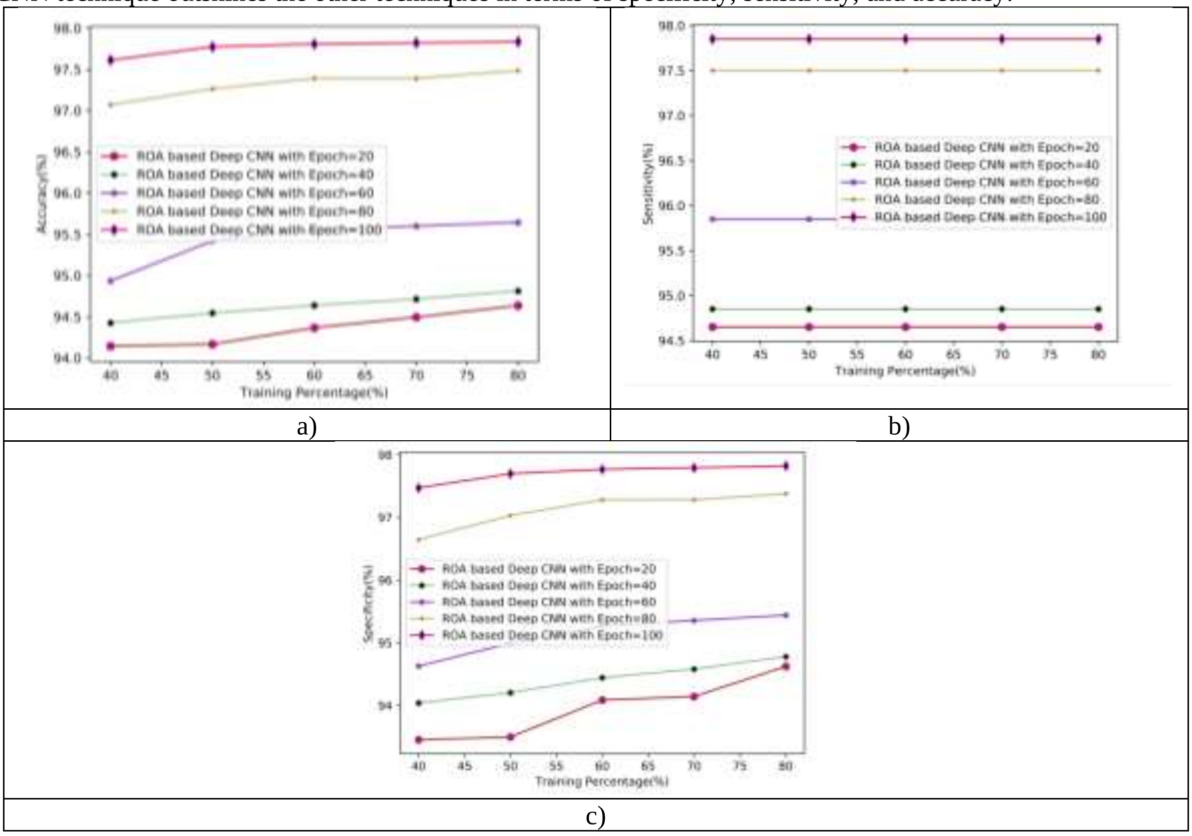
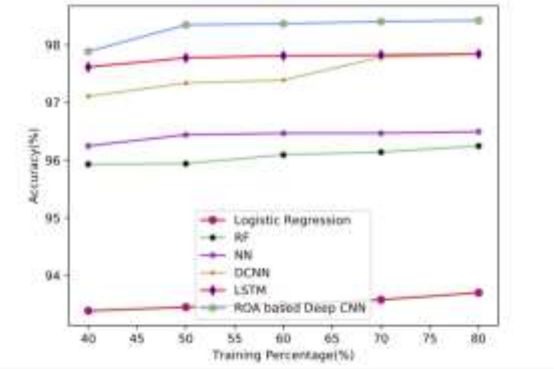


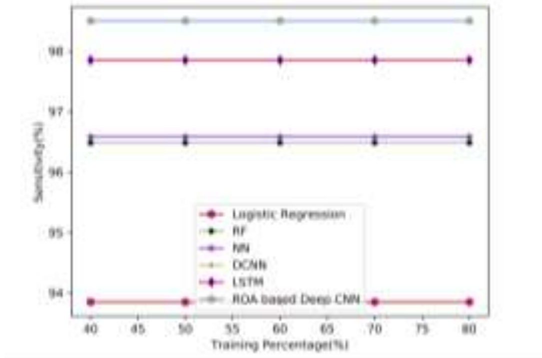
Figure 5. Performance analysis of ROA-based deep CNN in terms of: a) accuracy, b) sensitivity and c) specificity

5.6 Comparative analysis of the arrhythmia classification methods

This section comprises the comparative analysis of proposed ROA-based deep CNN technique. The proposed ROA-based deep CNN is compared with most prominent methods, such as Logistic regression technique, RF technique, Neural Networks, Deep Convolutional Neural Networks and LSTM. The primary parameters, such as specificity, accuracy and sensitivity are considered here for the analysis of the proposed ROA-based deep CNN method. The result of comparative analysis of the proposed ROA-based deep CNN with state-of-art technique is described in the figure 6. Comparative analysis of various existing methods with the ROA-based deep CNN in terms of accuracy is encompassed in figure 6 a).



a)



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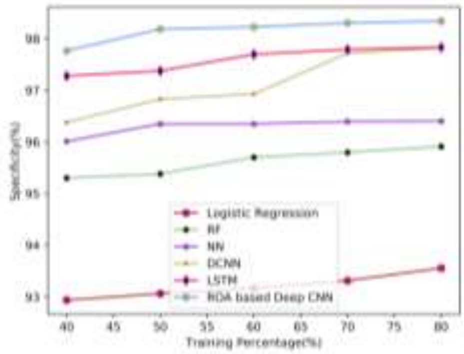

c)

Figure 6. Comparative analysis of various existing methods with the ROA-based deep CNN in terms of a) accuracy, b) sensitivity and c) specificity

From the figure 6 a), the LSTM method with 97.6% of accuracy is considered as the best accuracy range among the existing methods, but the proposed ROA-based deep CNN exceeds the performance of LSTM technique with the accuracy of 98.7%. The comparative analysis in terms of sensitivity is shown in the figure 6 b) and it is clear that the ROA-based deep CNN attains the highest sensitivity with 98.9%, which is far better than LSTM technique with 97.8% sensitivity. Figure 6 c) represent the comparative analysis of ROA-based deep CNN in terms of specificity, which shows that the existing LSTM achieves the specificity of 97.7%, which lags behind the proposed ROA-based deep CNN and the percentage improvement of the proposed ROA-based deep CNN is 1.013% with respect to LSTM. Overall, the proposed ROA-deep CNN outperforms all the other conventional techniques with respect to specificity, accuracy and sensitivity.

5.6 Comparative discussion

Table 1 shows the best performance of the various arrhythmia classification techniques. The best performance of existing methods and proposed ROA-based CNN methods are listed in the table 1. The best performance of the methods with respect to the metrics, such as sensitivity, accuracy and specificity is recorded at 80% of training. The table 1 shows that the LSTM method, which is a widely implemented technique for the arrhythmia classification attains only 97.6% of accuracy and 97.8% of sensitivity and 97.7% of specificity, whereas the proposed ROA-based deep CNN yields the accuracy of 98.7%, sensitivity of 98.9% and the specificity of 98.8%, which shows 1.1145% of performance improvement. From the Table 1, it is clear that the proposed ROA-based deep CNN exceeds the other conventional methods in terms of sensitivity, accuracy, and specificity.

Table 1. Comparative Discussion of the arrhythmia classification models

Methods	Accuracy	Sensitivity	Specificity
ROA-based deep CNN	98.7%	98.9%	98.8%
LSTM [3]	97.6%	97.8%	97.7%
DCNN [5]	97.6%		97.7%
NN[36]	96.4%	96.6%	96.1%
RF[34]	96%	96.5%	95.7%
Logistic regression [35]	93.6%	93.8%	93.7%

6. CONCLUSION

In this research, an efficient and automatic arrhythmia classification using the ROA-based deep CNN is carried out in the IoT platform for the real-time analysis of arrhythmia, which reduces the mortality rate of the patients suffering from heart problems, like arrhythmia. Moreover, ECG signals as the significant modality for arrhythmia classification is justified through the comparative analysis. The ECG signals from the patients are collected through the IoT nodes, which is communicated through the physician for the immediate and real-time diagnosis. The effective diagnosis is decided through the classification of arrhythmia, which is performed using the proposed optimized deep CNN that automatically extracts the confine features and yields the dimensionally reduced feature to the output layer such that the training time is minimized and classification accuracy is improved compared with the existing models. Moreover, in order to obtain an efficient classification outcome, the ROA is utilized in this research, which boosts the classifier performance through a perfect hyper-parameter tuning. The experimental analysis shows that the proposed ROA-based deep CNN attains the best accuracy, sensitivity and specificity of 98.7%, 98.9% and 98.8% when the epoch is 80. In future, any hybrid optimizations will be developed and highly advanced classifiers shall be employed for identifying arrhythmia in patients.

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