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Iot-Based Patient ECG Monitoring for Arrhythmia Classification via Optimized Deep Convolutional Neural Network

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Abstract - *Cardiac arrhythmia is one of type of cardiovascular disease (CVDs), which reports 12% of total deaths all over the world. Even though there is a lot of growth in IoT health monitoring, the manual method suffers from a lot of drawbacks. Hence, there is a need for an automatic method in health care specifically, for the classification of arrhythmia, for which an optimized deep convolutional neural network will be proposed. The IoT network will be simulated for collecting the ECG signals from the patients, and the signals will be processed the for classification of arrhythmia in patients, which assures continuous health monitoring of patients. The proposed model named optimized deep convolutional neural network will be implemented and compared with the existing methods in order to reveal the effectiveness based on the performance metrics, such as accuracy, sensitivity, and specificity.*

***Key Words*:** ECG, ROA, CNN, Epoch

1.INTRODUCTION *(Size 11, Times New roman)*

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The function of the heart is to pump blood enriched with oxygen all over the body and collect the impure blood with carbon dioxide and other wastes back from the body. An electrical impulse is produced by the sinoatrial node (natural pacemaker) present in the right atrium of the heart. This impulse is a rhythm that controls the rhythm of the heart. The electrical activity of the rhythm over a period of time is shown in a graphical record called an electrocardiogram (ECG). ECG helps in finding the condition of the heart [6]. Normally, an ECG is represented as a waveform in PQRST pattern with peaks and valleys. One cycle of the waveform pattern of normal heart rhythm is called sinus rhythm. This consists of deflections, which represent the events of the atria and the ventricles of the heart. The amplitudes of the P wave, QRS complex, S wave, T wave, and the intervals namely RR, PR, QT, and QRS complex are important measures, indicating the condition of the heart. Variations in these measures from the normal value are an indication of irregular rhythm called as Arrhythmia [1]-[6]. Cardiac arrhythmia (a.k.a dysrhythmia) is a condition of irregular heartbeat, which causes a sudden life loss of the patient [8] [2]. To overcome this sudden life loss, the cardiac behavior of the arrhythmia patients has to be monitored continuously to provide an appropriate medical procedure, for which the smart healthcare plays a major role [5]. Smart healthcare systems are the collection of medical devices, sensors, services, and applications that connect and communicate through the internet [9] [10]. Such frameworks have helped to provide quality healthcare and handle the constant increase in the demand for healthcare services [11] [12]. One such application is the development of a smart healthcare system for the accurate and real-time detection of life-threatening cardiac ailments [13] [14] [5]. Nowadays, Internet of things (IoT) plays a vital role in real-time monitoring of the modern healthcare domain. Supervision and access to medical care are the main pillars of any medical health (m-health) with a substantial reduction of the cost of monitoring with early detection and prevention [15] [2]. The collection of the ECG signals from the patient is done through the IoT network in such a way that at the remote the extraction of features from the ECG signal is done and the machine learning approaches are used, which are the important steps in the development of automated detection of arrhythmia [5]. In the last few decades, various feature extraction and classification approaches have been extensively used for the accurate detection of arrhythmias. The features namely, complexity measure (CPLX) [19], threshold crossing intervals (TCI) [18], VF filter leakage measure (VFF) [20], and the auto-correlation function (ACF) [21] coupled with various machine learning based classifiers have been widely used for the automated detection of arrhythmia using the ECG signals. Similar works include, the extraction of features based on the spectral algorithm (SPEC) [22], phase space representation (PSR) [23], and wavelet transforms [16] [17] [5].

Many research attempts have been made to provide solutions for automated heartbeat classification. The existing methods are roughly divided as feature-engineering-based and deep-learning-based methods. However, none of these methods has achieved clinical significance. Most feature-engineering methods are facing a bottleneck of applying a standalone classifier and using a static feature set to classify all heartbeat samples [24]. This has been shown to cause huge impact on the identification of problematic heartbeats. The deep-learning-based methods are commonly limited to learning temporal patterns from the raw ECG heartbeats only. The frequency patterns and the RR intervals have not been well considered to assist the classification. Moreover, to supply sufficient training data for driving the deep neural networks, many works [25] followed a biased evaluation procedure, in which they synthesized heartbeat samples from the whole dataset and then randomly split all heartbeats for model training, validation and testing. Consequently, heartbeats from the same patient are likely to appear in both the training and test datasets, leading to an overestimation of the model performance. The over-optimistic results may hide potential limitations of the neural networks [1]. Generally, traditional and deep learning techniques are the two principal types of procedures to detect arrhythmia. Traditional methods utilize hand-engineered features and employ different classification algorithms such as K-Nearest Neighbour [26], Random Forest [26], and Support Vector Machines [27]. Moreover, many recent studies try to learn neural networks for arrhythmia detection [28]. With the advent of deep learning, most recent researches try to tackle the problem of arrhythmia detection by applying a convolution neural network (CNN), the dominant branch of deep learning models [3].

2. **Existing System**

The existing methods reviewed in the previous section reveals that the performance degradation occurs due to the improper training and concept drifts occur due to the inter-personnel variations of the ECG signals. Figure 1 shows the existing model. The ECG signals are pre-processed and the features are extracted from the ECG signals. The features are employed for training the classifiers, such as Multi-layers perception, Support vector machine (SVM), Linear SVM, Bayesian model with Gaussian kernel, Decision tree, K-nearest neighbors model, Deep convolutional neural network, LSTM recurrent networks, and Actor critic neural networks and these classifiers are used reported in papers [1]- [6].

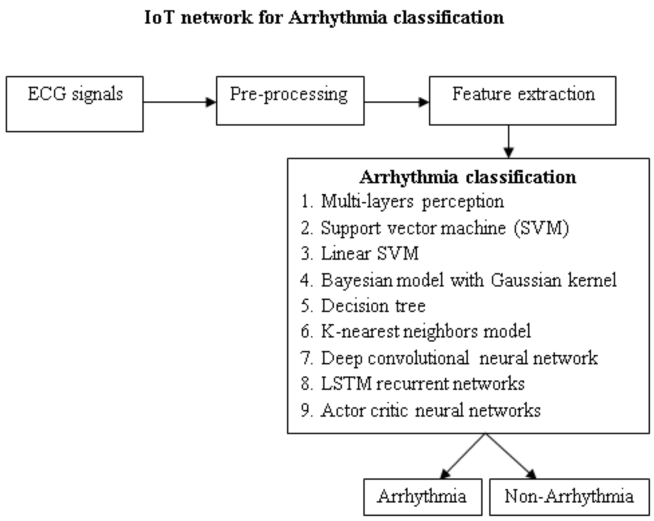

Fig 4.1: IoT Network for Arrhythmia Classification

3. **Proposed System with 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.

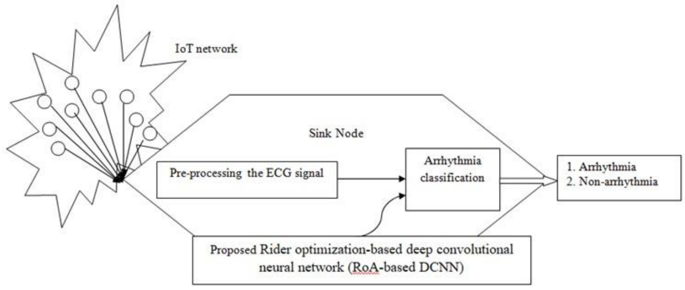

Fig 5.1: Deep learning-based model for arrhythmia classification using the ECG signals of the patients.

4. **Result and Discussion:**

Figure 4 manifests the obtained ECG signals of the arrhythmia patient, which are transmitted to the physician in any part of the world. This enables the physician to examine and analyse the ECG signal and provide on-time medical support. The physician analyses 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 a 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) signify the communication of the ECG signals with the physician and the patient.

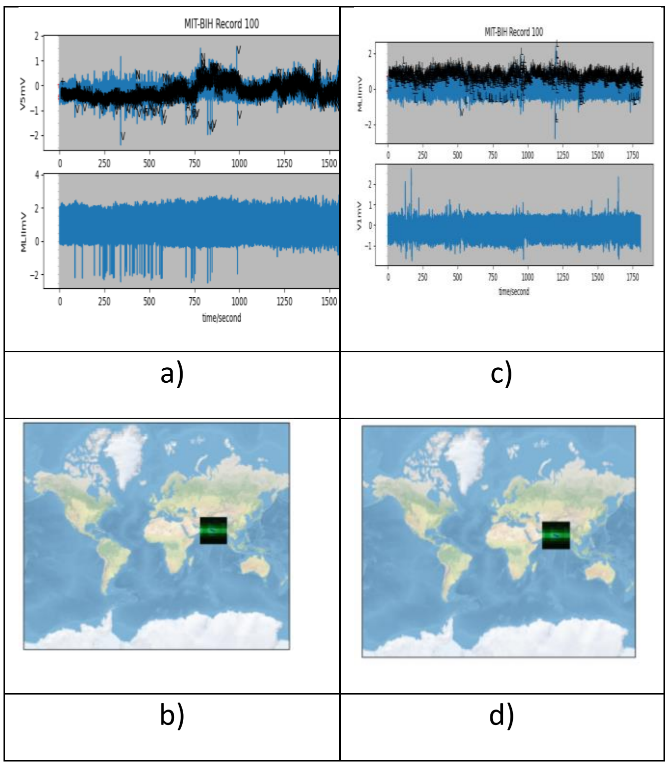

Figure 4. Experimental analysis of the proposed ROA-based deep CNN a) sample ECG signal-1, b) Signal communication of signal-1 with the Physician, c) sample ECG signal-2, and d) Signal communication of signal-2 with the Physician

It is clear that the accuracy of the proposed ROA-based deep CNN technique is increased with an 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 the 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 at 80%. From this figure 5 a), it is evident that the proposed ROA-based deep CNN surmounts the other state-of-art technique in terms of accuracy with 80% of training. 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 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.

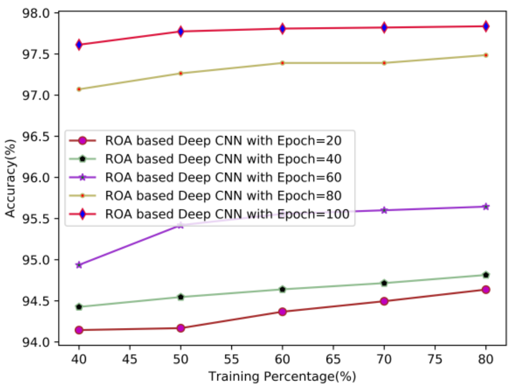

Figure 5(a): Performance analysis of ROA-based deep CNN in terms of: a) accuracy

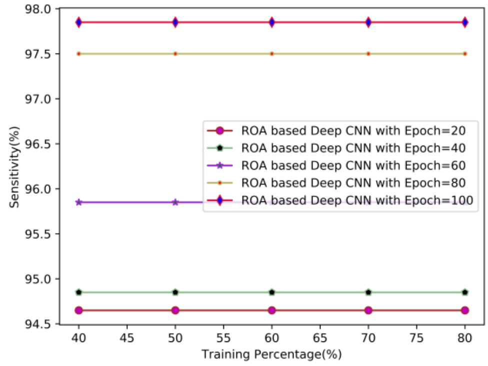

Figure 5(b): Performance analysis of ROA-based deep CNN in terms of: b) sensitivity

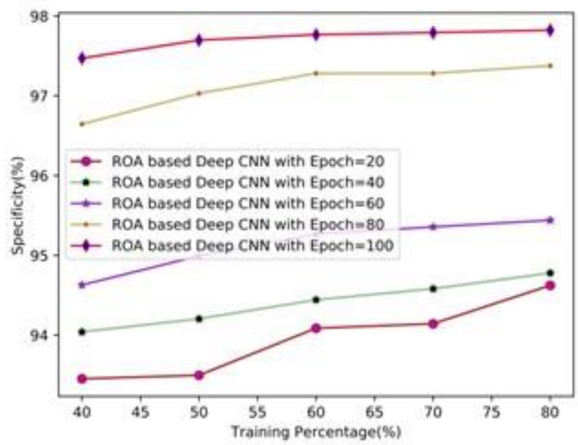

Figure 5(c): Performance analysis of ROA-based deep CNN in terms of c) specificity

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.

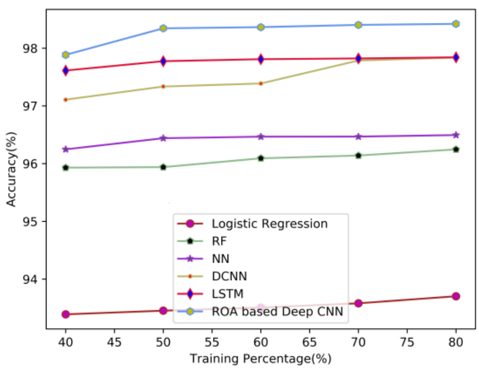

Figure 6(a). Comparative analysis of various existing methods with the ROA-based deep CNN in terms of a) accuracy

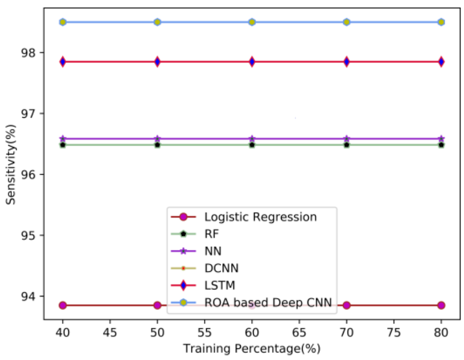

Figure 6(b). Comparative analysis of various existing methods with the ROA-based deep CNN in terms of b) sensitivity

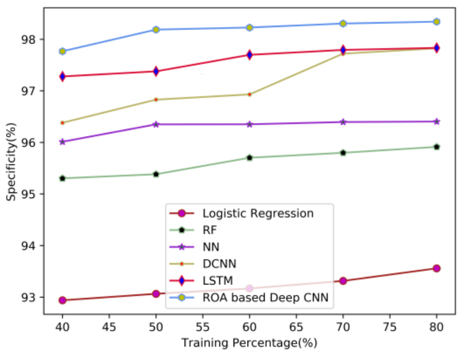

Figure 6(c). Comparative analysis of various existing methods with the ROA-based deep CNN in terms of c) specificity

The below-mentioned table defines a comparative result of accuracy, sensitivity, and Specificity in table no. 1

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%

5. CONCLUSIONS

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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