IoT-Based Patient ECG Monitoring for Arrhythmia Classification Via Optimized Deep Convolutional Neural Network

Mr. Aniket Sonawane[1], Prof. Surabhi Tankkar[2]
Department of Electronics & Telecommunication Engineering, Alamuri Ratnamala Institute of Engineering and Technology

DOI: 10.5281/zenodo.4400661
https://zenodo.org/record/4400661#.X-xoM9gzaMo

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

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) [12], 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) [12], phase space representation (PSR) [13], 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 a clinical

ISSN 2348-0831

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 . This has been shown to cause huge impacts on identification of the problematic heartbeats. The deep-learning based methods are commonly limited by 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 [15] 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 test. Consequently, heartbeats from the same patient are likely to appear in both the training and test datasets, leading to an over estimation of the model performance. The overoptimistic 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 [16], Random Forest [16], and Support Vector Machines. Moreover, many recent studies try to learn neural networks for arrhythmia detection. 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. LITERATURE REVIEW

S.No.	Authors	Methods	Advantages	Drawbacks	Achievement
1	Jinyuan He, *et al.* [1]	Dynamic Heartbeat Classification with Adjusted Features (DHCAF) and Multi-channel Heartbeat Convolution Neural Network (MCHCNN)	Utilizes the temporal and frequency patterns from heartbeat in order to assist effective classification	Heartbeat rhythms are not integrated well to the network and also it can be easily affected by other learned features.	Accuracy of 91.4%
2	Rajendran Sree Ranjani [2]	Machine learning	IoT and machine learning equipped system offer observations and recordings for a longer period of time, and this continuous monitoring prevents the severity of arrhythmia. This method accurately classifies the arrhythmia patients effectively from a remote distance	However, early detection and accurate diagnosis of arrhythmia patients is dependent on the additional health parameters irrespective of ECG	Accuracy of 97.2%
3	Adeleh Bitarafan *et al.* [3]	LSTM Recurrent Networks	Permits modeling the relation among different heartbeats in a sequence. Due to not considering any expert knowledge, and automatically segmenting and classifying ECG signals, the DCNN-LSTM-b version of our model has a strong potential to be applied in real-time as well as the real-world applications	we could carry out the experiment only under the weighted cross-entropy loss	Accuracy of 98.93%
4	Anoop Vylala & Bipin Plakkottu Radhakrishnan [4]	Taylor-Sine Cosine Algorithm (Taylor-SCA)-actor-critic neural network	Utilization of the time-based and frequency-based features ensures the robustness and accuracy of classification	The future dimension focussed on any deep learning method	accuracy of 95.45%
5	Rohan Panda, *et al.* [5]	FFREWT Filter-bank and Deep Convolutional Network	Multiscale analysis of ECG is enabled	Requires more ECG episodes in the training to obtain optimal kernel, weight, and bias parameters	average accuracy of 97.59%

6	Maheswari Arumugam and Arun Kumar Sangaiah [6]	wavelet-based algorithm	This method can be employed to find the arrhythmia affected population quickly and give treatment to them instantaneously instead of creating chaos and panic in patients not having heart ailments. Another advantage of the proposed method is that the ECG signal details utilize ideal time-frequency resolutions.	Requires a machine learning or deep learning-based solution	accuracy of 95.92%

3. PROBLEM STATEMENT

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

- Although deep learning methods have made remarkable progress, they still face huge challenges. The morphological characteristics of ECG signals can vary greatly among different individuals (or patients), which may cause severe performance degradation to the existing models when tested in inter-patient paradigm. The discrepancy between training and test data, referred to as domain shifts, may violate the basic independent identically distributed (I.I.D) assumption in learning-based schemes and is common in reality [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 actor critic neural network, where the training model is deliberated, but there exist 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.

4. PROPOSED METHODOLOGY

The ultimate intention of the research will be to design and develop a deep learning-based model for arrhythmia classification using the ECG signals of the patients. The main purpose is to develop a smart health monitoring, where the ECG signals from the patients at the remote location will be communicated to the doctor, where the steps of diagnosis will take place. The ECG signals from the patients will be collected using the IoT nodes and will be sent to the sink node for classification, such that the results of the final diagnosis will be executed. The steps of IoT-arrhythmia classification will be: 1) Pre-processing and 2) Arrhythmia classification. For diagnosis, initially, the ECG signals collected by the IoT nodes will be pre-processed in such a way that the signal will be made fit for the further processes associated with the arrhythmia classification. Then, the second step will be the arrhythmia classification, where the features of the ECG signals will be fed to the proposed Rider optimization-based deep convolutional neural network (RoA-based DCNN), which will classify the features from ECG signal to identify the abnormality in the heart beat of the individual. The proposed RoA-based DCNN will be developed through the integration of the Rider optimization algorithm (ROA) in the DCNN classifier, which will tune the internal model parameters of DCNN classifier in such a way to boost the classification performance and avoid the drifts that occur due to the variation in the ECG signals between the individuals. The output from the classification model will be arrhythmia or non-arrhythmia. The method will be implemented in PYTHON and the analysis will be done. The database used for the implementation will be the MIT-BIH database and the implemented model will be analyzed and will be compared with the existing methods in order to reveal the effectiveness of the developed method. For simulation, the ECG signals will be randomly assigned at the different nodes in the IoT network and then, the year-wise and month-wise data will be generated. Once the simulation is completed in the PYTHON, the protocols will be evaluated through the performance metrics, such as accuracy, sensitivity, and specificity with respect to the month and year. Figure 1 block diagram of the proposed classification model. The comparative methods used will be [3], [4], and [5] and the GUI of the modules will be demonstrated.

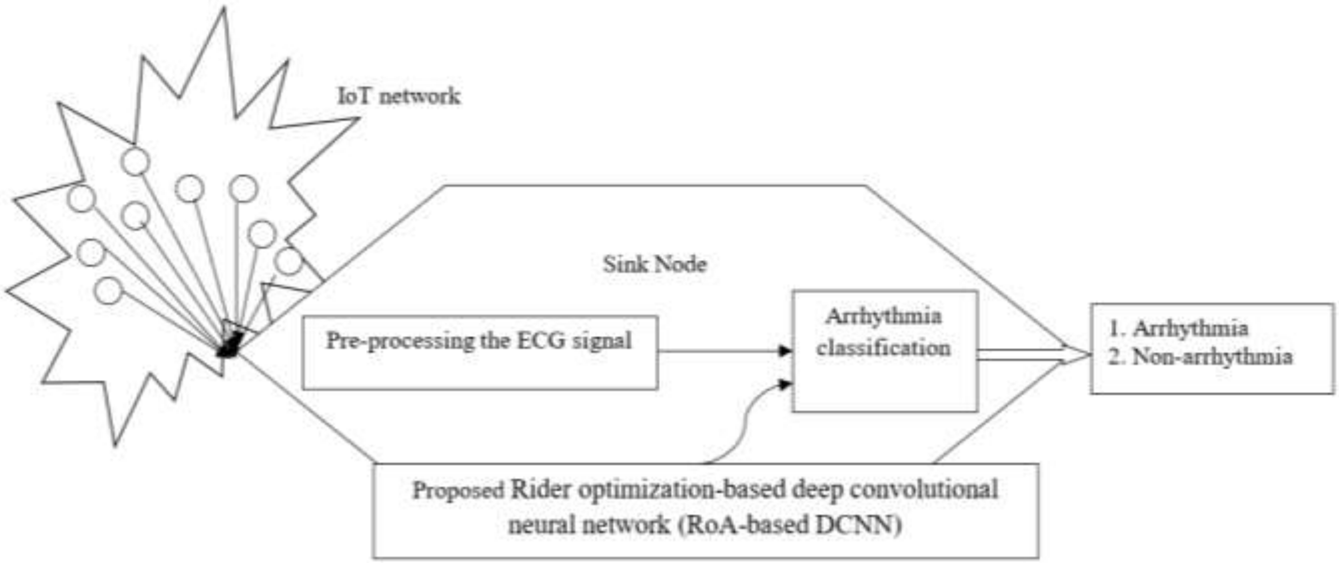

Figure 1. Block diagram of our approach

5. CONCLUSION

In this paper, 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 optimized deep convolutional neural network

6. REFERENCES

[1] Jinyuan He, Jia Rong, Le Sun, Hua Wang, Yanchun Zhang & Jiangang Ma, " A framework for cardiac arrhythmia detection from IoT-based ECGs", World Wide Web, vol.23, pp.2835–2850, 2020.
[2] Rajendran Sree Ranjani, "Machine Learning Applications for a Real-Time Monitoring of Arrhythmia Patients Using IoT", Internet of Things for Healthcare Technologies, vol.73, pp 93-107, 09 June 2020.
[3] Adeleh Bitarafan ; Afra Amini ; Mahdieh Soleymani Baghshah ; Hamidreza Khodajou-Chokami, " A Hybrid Deep Model for Automatic Arrhythmia Classification based on LSTM Recurrent Networks", 2020 IEEE International Symposium on Medical Measurements and Applications (MeMeA), 1 June-1 July 2020.
[4] Anoop Vylala & Bipin Plakkottu Radhakrishnan, " Spectral feature and optimization- based actorcritic neural network for arrhythmia classification using ECG signal", Journal of Experimental & Theoretical Artificial Intelligence, vol.32, no.3, pp.409-435, 27 Jul 2020.
[5] Rohan Panda, Sahil Jain, RK Tripathy, and U. Rajendra Acharya, "Detection of shockable ventricular cardiac arrhythmias from ECG signals using FFREWT filter-bank and deep convolutional network", Computers in Biology and Medicine, vol.124, September 2020.
[6] Maheswari Arumugam Arun Kumar Sangaiah, "Arrhythmia identification and classification using wavelet centered methodology in ECG signals", Wiley Online Library, 07 November 2019.
[7] Ming Chen; Guijin Wang; Zijian Ding; Jiawei Li; Huazhong Yang, "Unsupervised Domain Adaptation for ECG Arrhythmia Classification", In Proceedings of the 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), 20-24 July 2020.
[8] Krasteva, V., & Jekova, I, "QRS template matching for recognition of ventricular ectopic beats", Annals of Biomedical Engineering, vol.35, no.12, pp.2065–2076, 2007.
[9] S. R. Islam, D. Kwak, M. H. Kabir, M. Hossain, and K.-S. Kwak, "The internet of things for health care: a comprehensive survey," IEEE Access, vol. 3, pp. 678–708, 2015.
[10] M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. P. Zaveri, "eseiz: An edge-device for accurate seizure detection for smart healthcare," IEEE Transactions on Consumer Electronics, vol. 65, no. 3, pp. 379–387, 2019.
[11] M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. P. Zaveri, "Neuro-detect: A machine learning-based fast and accurate seizure detection system in the iomt," IEEE Transactions on Consumer Electronics, vol. 65, no. 3, pp. 359–368, 2019.
[12] L. Rachakonda, S. P. Mohanty, E. Kougianos, and P. Sundaravadivel, "Stress-lysis: A dnn-integrated edge device for stress level detection in the iomt," IEEE Transactions on Consumer Electronics, vol. 65, no. 4, pp. 474–483, 2019.
[13] C. Li, X. Hu, and L. Zhang, "The iot-based heart disease monitoring system for pervasive healthcare service," Procedia computer science, vol. 112, pp. 2328–2334, 2017.

[14] Z. Yang, Q. Zhou, L. Lei, K. Zheng, and W. Xiang, "An iot-cloud based wearable ecg monitoring system for smart healthcare," Journal of medical systems, vol. 40, no. 12, pp.286, 2016.

[15] Niewolny, D, "How the internet of things is revolutionizing healthcare, freescale semiconductors", In Proceedings of International Conference on Healthcare, pp. 211–219, 2013.

[16] M. Sharma, R.-S. Tan, and U. R. Acharya, "Detection of shockable ventricular arrhythmia using optimal orthogonal wavelet filters," Neural Computing and Applications, vol.32, pp.15869–15884, 2020.

[17] M. Sharma, S. Singh, A. Kumar, R. San Tan, and U. R. Acharya, "Automated detection of shockable and non-shockable arrhythmia using novel wavelet-based ecg features," Computers in Biology and Medicine, vol. 115, p. 103446, 2019.

[18] N. V. Thakor, Y.-S. Zhu, and K.-Y. Pan, "Ventricular tachycardia and fibrillation detection by a sequential hypothesis testing algorithm," IEEE Transactions on Biomedical Engineering, vol. 37, no. 9, pp. 837–843, 1990.

[19] X.-S. Zhang, Y.-S. Zhu, N. V. Thakor, and Z.-Z. Wang, "Detecting ventricular tachycardia and fibrillation by complexity measure," IEEE Transactions on biomedical engineering, vol. 46, no. 5, pp. 548–555, 1999.