IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⩸ Impact Factor 7.39 ⩸ Vol. 11, Issue 6, June 2022

DOI: 10.17148/IJARCCE.2022.11693

Artificial Intelligence of Things Wearable System for Cardiac Disease Detection

Devi Kannan[1], Nishitha D[2]

[1]Assitant Professor, Dept. of Computer Science and Engineering, Bangalore

[2]Student, Dept. of Computer Science and Engineering, Bangalore, Karnataka, India

Abstract: This study suggests an electrocardiogram (ECG) analysis and heart illness detection artificial intelligence of things (AIoT) system. A cloud database, a user interface on a smart device application (APP), front-end IoT-based hardware, and an AI platform for heart illness diagnosis are all included in the system. The wearable ECG patch with an analogue front-end circuit and a Bluetooth module, which is the front-end IoT-based hardware, can detect ECG signals. The APP on smart devices may identify diseases in real time and classify odd signals in addition to displaying users' real-time ECG readings. The cloud database will receive these ECG signals. Each user's ECG readings are stored in the cloud database, creating a big-data set that an AI programme may use to identify heart problems. The convolutional neural network-based approach that this study suggests has an average accuracy of 94.96 percent. The Ministry of Health and Welfare's Tainan Hospital provided the ECG dataset used in this investigation. Additionally, a cardiologist additionally carried out signal verification.

Keywords: Arrhythmia, atrial fibrillation, convolutional neural network, electrocardiogram, artificial intelligence of things, wearable device, application, cloud server.

1. INTRODUCTION

The most common reason for heart disease is arrhythmia. It may be categorized into three groups: bradycardia, tachycardia, and premature heartbeat. Atrial fibrillation is the main cause of acute stroke, and ventricular tachycardia is the main cause of shock or sudden cardiac death, even though the majority of arrhythmias do not pose an immediate risk and often occur in daily life.

The World Health Organization reports that arrhythmias are responsible for around 15% of fatalities globally. Meanwhile, cardiovascular illnesses account for over 80% of sudden fatalities. The leading cause of mortality for those with cardiovascular problems is arrhythmia. In the USA in 2050 and Europe in 2060, respectively, there will be 12 and 17.9 million persons who have atrial fibrillation. Users being able to attach a wearable monitoring device, which can detect aberrant electrocardiogram (ECG) signals and immediately send a warning message to the hospital, can stop many tragedies from occurring for the sake of everyday health care in an ageing society.

This study develops a convolutional neural network (CNN)-based system for classifying heart diseases and focuses on a number of common arrhythmias. Additionally, a cloud database, a user interface on application (APP), and wearable Internet of Things (IoT) hardware are coupled to create an artificial intelligence (AI) health-care platform.

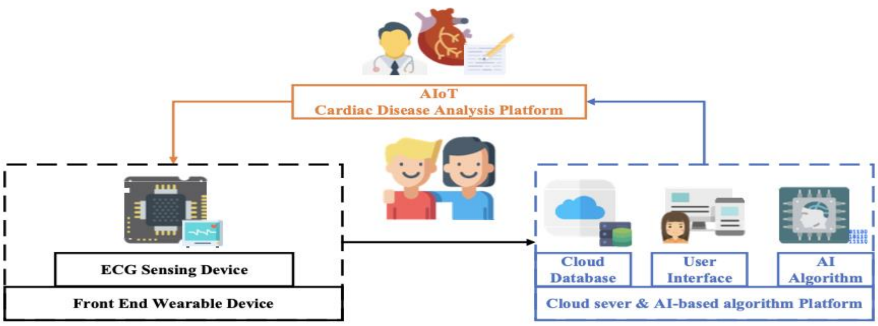


Fig 1. System block of ECG signal acquisition and application

DOI: 10.17148/IJARCCE.2022.11693

2. SYSTEM OVERVIEW

The study's proposed artificial intelligence of things (AIoT) platform (Fig. 1) intends to analyze real-time ECG readings to lower the likelihood of life-threatening arrhythmias. The following sections present and describe a complete system structure for real-time detection, low power consumption, and extended use, which includes a wearable front-end ECG sensing device, a user interface on smart device APP, a cloud database, and an AI-based algorithm for cardiac disease analysis.

A. Wearable ECG monitoring device

This work suggests sensing hardware architecture, as seen in Fig. 2, that consists of a commercial power management integrated circuit (IC), a commercial Bluetooth module, and an analogue front-end circuit with low power consumption. The self-designed system on chip (SOC) for the analogue front-end circuit contains a level shifter, a 10-bit sigma-delta analogue to digital converter, and digital signal processing units. The front-end SOC's ECG signal is gathered by the commercial Bluetooth module, which uses Bluetooth Low Energy 4.0 to communicate it instantaneously to the APP. The wearable ECG monitoring equipment has a single lead and two moist silver chloride electrodes that are affixed to the chest. Under typical conditions, it may be worn for up to 24 hours.

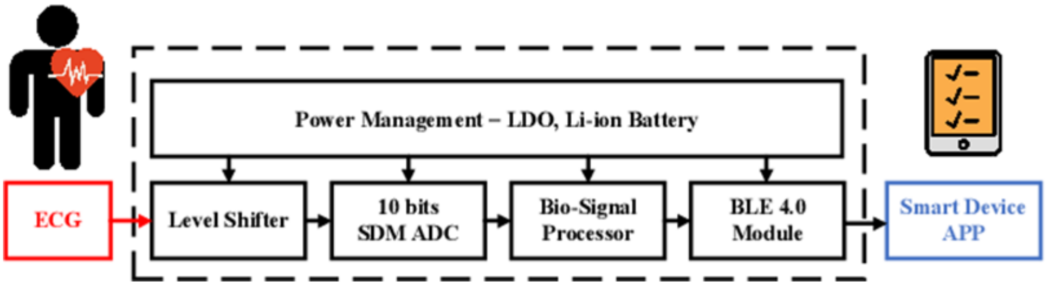


Fig 2. Front-end device block of the implemented ECG acquisition

B. User interface on smart device APP

A user interface for an APP is also suggested, and the layout is depicted in Fig. 3. It consists of three primary components: an ECG display function, an AI-based arrhythmia analysis function, and a function for storing and transferring data. The user's ECG signal will be shown on the screen in real-time, and the AI system will be utilized to simultaneously categorizes it into several cardiac arrhythmias. Modern mobile devices have powerful computational capabilities, thus the categorization on smart devices just displays two categories: normal and abnormal. To further classify the user's ECG data and determine a more exact arrhythmia type, the classification will be finished on a cloud server. The gathered ECG data will be transferred to a cloud database in addition to being kept on local mobile devices. All data will be encoded and given time stamps to ensure data accuracy and safety.

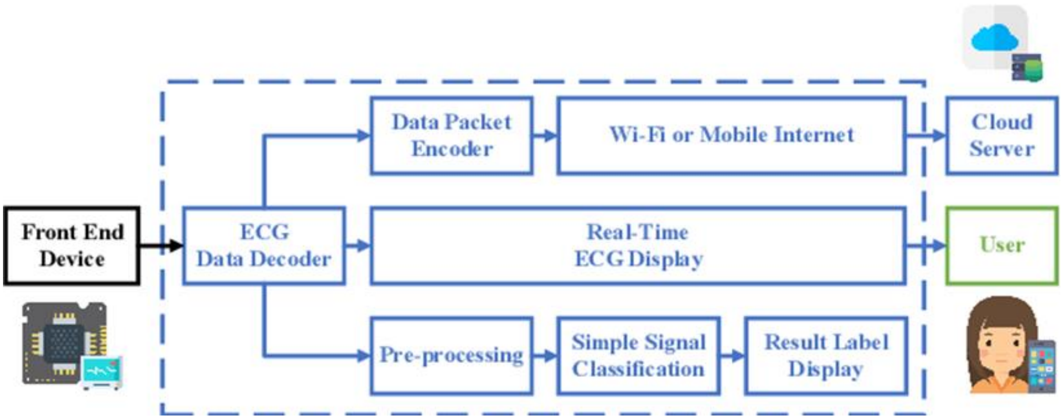


Fig 3. The smart device APP structure

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⁜ Impact Factor 7.39 ⁜ Vol. 11, Issue 6, June 2022

DOI: 10.17148/IJARCCE.2022.11693

C. Cloud server and database

Figure 4 depicts the design of the cloud server and database. This server houses a big-data database with three components: data storage, a web user interface, and an AI-based arrhythmia analysis algorithm. Prior to decoding the data packages into ECG signals, the data storage is responsible for receiving the data packages from the front-end smart devices. The measured items and the measurement time stamps will also be used to categorize the ECG signals for storage. Second, the online user interface offers a clear information platform for doctors, patients, and patients' relatives. With the use of the saved ECG data, doctors may make more accurate diagnoses of their patients' conditions, while patients and their family can learn more about their daily ECG signal. Third, the AI-based method can quickly identify out-of-the-ordinary signals from a big volume of data. A typical human produces over 100,000 heartbeats every day, the most of which are normal ECG signals with just a small minority being aberrant. This makes it extremely difficult for clinicians to make an accurate diagnosis using long-term ECG data. The AI-based system can swiftly identify anomalous signals using this cloud platform, and these signals will be shown on the online user interface.

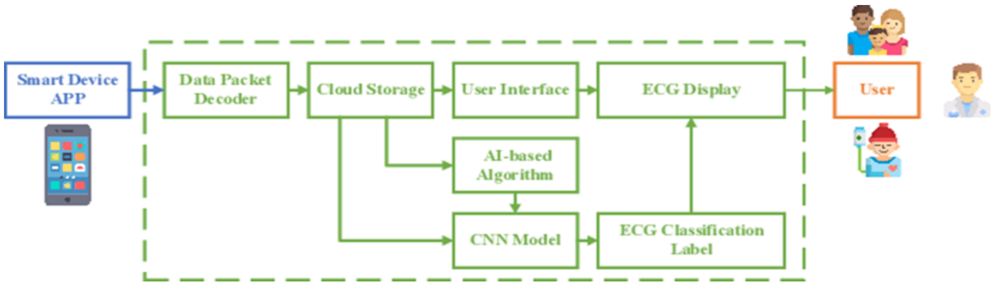


Fig 4. The cloud sever and database structure

D. AI-based algorithm for arrhythmia classification

According to Fig. 5, the AI-based method for classifying arrhythmias contains four categories: normal ECG, atrial fibrillation, atrial flutter, and ventricular fibrillation. The CNN model and data pre-processing are the two components that make up this algorithm's structure. Traditional ECG signal processing techniques such time-frequency analysis, feature extraction, and R-peak and QRS complex identification are not used to improve the CNN model's feature learning. As illustrated in Fig. 6, the pre-processing structure suggested in this work consists of three steps: noise reduction, baseline removal, and picture synthesis. First, noise is removed using an 8-point moving average filter. The moving average filter's finite windows will take the signal into convolution. In order to lower the discrete-time noise and improve the identification of the peak value, the output signal in the filter range must also be averaged. An 8-point moving average filter is chosen after extensive testing and comparison.

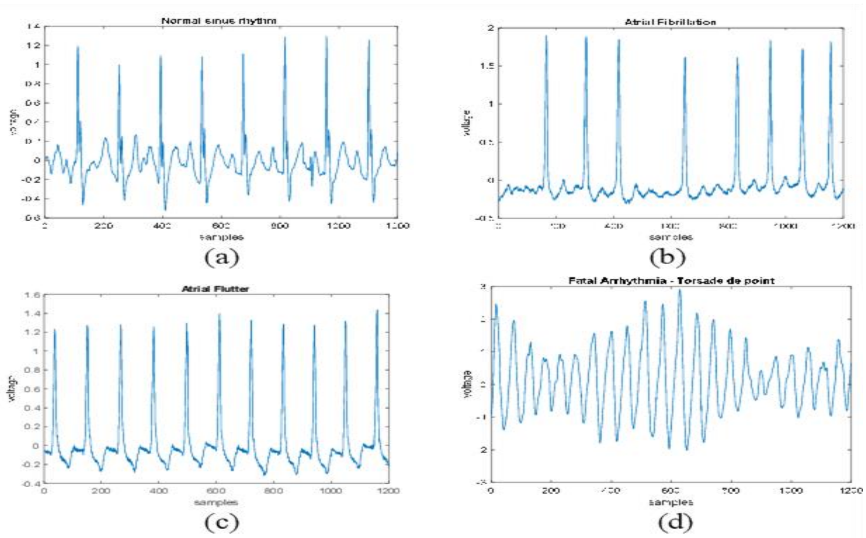


Fig 5. (a) normal ECG signal,(b) atrial fibrillation,(c) atrial flutter (d)ventricular fibrillation

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⋇ Impact Factor 7.39 ⋇ Vol. 11, Issue 6, June 2022

DOI: 10.17148/IJARCCE.2022.11693

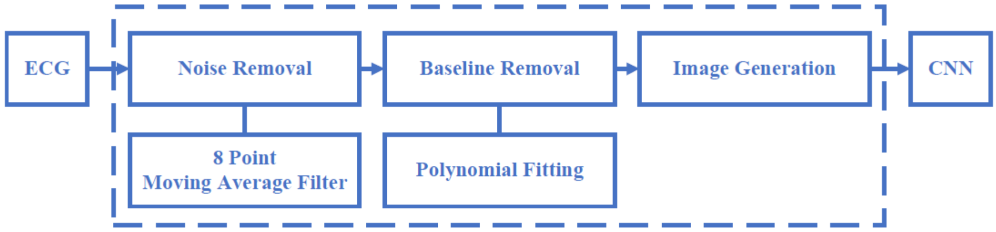


Fig 6. The pre-processing structure

Second, polynomial fitting is used to remove the baseline in order to resolve baseline drift. The idea is to insert a parametric curve to approximate the position of a known dataset, and then to subtract the fitted parametric signal from the actual signal to produce a baseline removed ECG signal. Third, the way picture creation is constructed mimics how cardiologists interpret ECG signals. Cardiologists typically take into account the time the abnormal ECG occurred and offer sustained and non-sustained analyses on the subsequent ECG. Cardiologists must make a specific notice if there are three aberrant heartbeats present or if the odd ECG signal lasts for more than 30 seconds. Using this idea as a foundation, the pre-processed signal will convert to pictures at a sample rate of 1200 Hz (approximately 4.8 s). Finally, these images will be the training, validation, and testing data of the CNN model in the next stage.

For feature extraction and classification, this work uses a CNN with a single dimension. The CNN model cannot be too complex to implement in order to actualize the CNN model through digital IC architecture in future development. The CNN model put out in this work has three fully linked layers in addition to the four convolutional layers. As the active function, a leaky rectified linear unit (leaky ReLU) is placed after each convolutional layer. Leaky ReLU can prevent many neurons from developing dead ReLU in addition to providing the advantages of regular ReLU. Additionally, some of the input data are negative, which can have some significant characteristics that shouldn't be disregarded. For the reasons listed above, a leaky ReLU is chosen as the active function. The neural network used in this investigation is seen in Fig. 7 in its structural layout. In order to extract more exact features, the model does a max pooling with stride equal to 1. Additionally, each input image's edge information requires the same amount of padding to be saved. Next, the three completely linked layers reduce the output neurons from 100 to 10, and from these 10 neurons, output is then limited to 4 categories. The first convolutional layer's filter order is set at 10 and doubled for each further layer. To extract the necessary characteristics, the 180 setting is applied to each filter kernel order. The optimizer employed by the model is gradient descent. The model also adjusts the learning rate, learning rate decay, and weight decay parameter to 0.0001, 0.1, and 0.9 after each epoch, respectively. Training data to validation data and test data are proportionately 8:1:1.

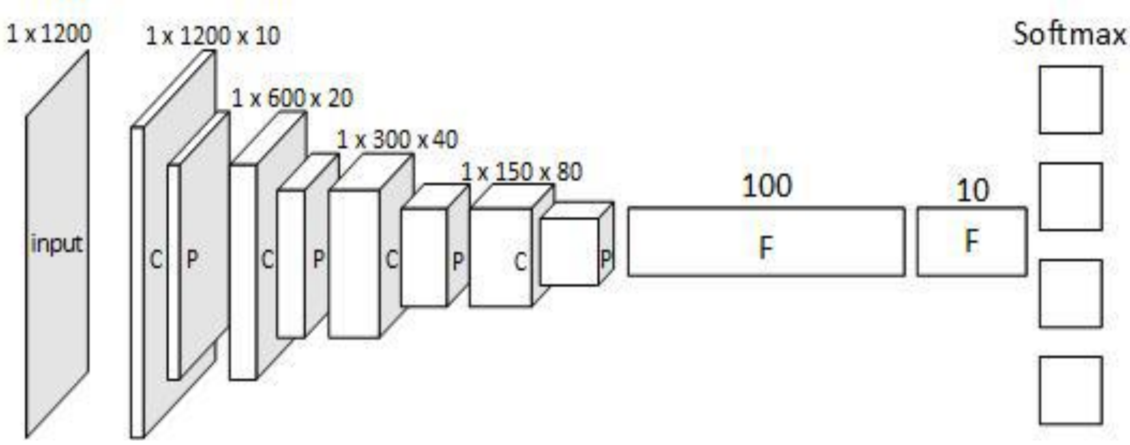


Fig 7. The neural network structure

ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified ⋇ Impact Factor 7.39 ⋇ Vol. 11, Issue 6, June 2022

DOI: 10.17148/IJARCCE.2022.11693

3. EXPERIMENTAL RESULT

Clinical experiments involving patients at Tainan Hospital, Ministry of Health and Welfare, are conducted as part of an application to the Ministry of Health and Welfare to validate this AIoT system. In these trials, each component—including the wearable ECG sensor, APP user interface, cloud server, and AI-based arrhythmia detection algorithm—will be put to the test.

A. Wearable ECG-sensing device

The front-end ECG-sensing device is seen in Fig. 8(a), and it measures 84.55 mm by 39.38 mm by 18.31 mm. A demonstration of how to operate the ECG-sensing device is shown in Fig. 8(b). The ECG measurement has a single lead and lasts for 24 hours.

(a) (b)

Fig 8. (a) The front-end sensing device (b) The actual ECG measurement

B. User interface on smart device APP

The suggested user interface for the APP is shown in Fig. 9. The user's ECG signal is shown in its raw form in the upper section, while the output results of the arrhythmia classification algorithm are shown in the lower part. Each ECG signal will be classified as either normal or abnormal.

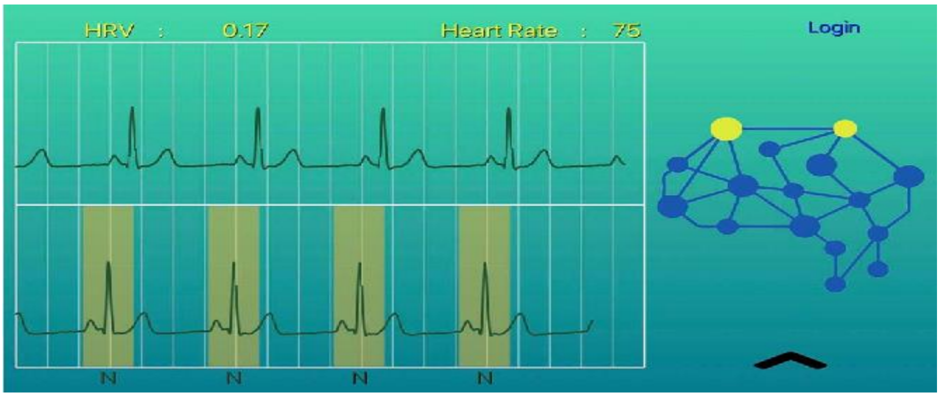


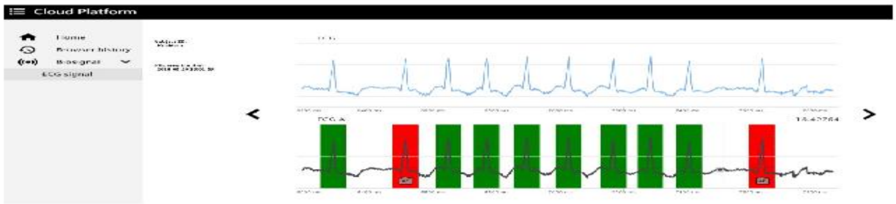
Fig 9. The proposed iOS APP screenshot

C. Cloud server and database

Figure 10(a) illustrates the online user interface that allows the user to get past ECG data so that they may speak with doctors in more detail. As can be seen in Fig. 10, the online user interface and the APP user interface are relatively comparable (b). The ECG raw data and output findings from the arrhythmia classification algorithm are also shown in the upper and bottom portions, respectively. Each ECG signal will be identified as several ECG kinds, such as various arrhythmia types, which is a little different from the APP's user interface.

International Journal of Advanced Research in Computer and Communication Engineering
ISO 3297:2007 Certified ⋇ Impact Factor 7.39 ⋇ Vol. 11, Issue 6, June 2022
DOI: 10.17148/IJARCCE.2022.11693

(a)



(b)

Fig 10. (a)&(b) The proposed WEB screenshot

D. AI-based algorithm for arrhythmia classification

Several data preparation functions are required in order to have an appropriate input dataset. First, Fig. 11 illustrates how the data with and without noise reduction differ. Applying an 8-point moving average filter allows for its realization. Second, polynomial fitting is used to finish the baseline removal. The outcome is depicted in Fig. 12.

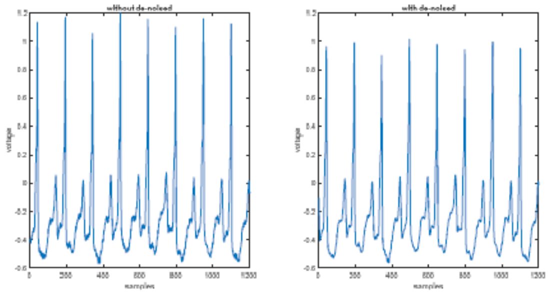


Fig 11. The result without(left)/with(right) noise removal

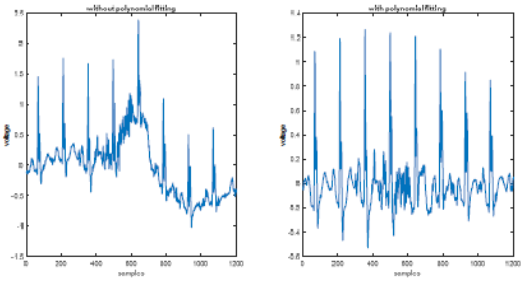


Fig 12. The result without(left)/with(right) baseline removal

In this paper, a one-dimension CNN is proposed. The CNN model is appropriately built with four convolutional layers and three fully linked layers, taking into account the potential of achieving this model through digital IC design and the outcomes of several tests. The weight decay parameter, learning rate, and learning rate decay parameter have been adjusted at 0.0001, 0.1, and 0.9 after each epoch, respectively, based on several testing. The suggested CNN model handles both the dataset from MITBIH and the data from clinical trials. Tables I and II present the findings. Clinical trial data and the dataset from MIT-BIH had average accuracy rates of 95.73 percent and 94.96 percent, respectively. Table III displays comparisons between this study and earlier research.

DOI: 10.17148/IJARCCE.2022.11693

TABLE I. OPEN SOURCE DATABASE TESTING RESULT

	NSR	Afib	Afl	FA	Accuracy
NSR	272	9	0	0	96.69%
Afib	15	371	3	0	95.37%
Afl	9	1	69	1	93.24%
FA	0	0	0	7	100%

TABLE II. CLINICAL TRIAL DATABASE TESTING RESULT

	NSR	Afib	Afl	FA	Accuracy
NSR	9531	130	15	17	98.35%
Afib	16	249	9	5	89.24%
Afl	0	0	0	0	-
FA	0	0	0	0	-

TABLE III. PERFORMANCE COMPARSION

	This work	2017[4]	2016[5]	2016[6]
Classification target	NSR, Afib, Afl, FA	NSR, Afib, Afl, Vfib	NSR, Afib, Afl, Vfib	Afib, Afl, Vfib
Model	CNN	CNN	Rotation forest	Decision tree
Accuracy	Clinical trial testing is 94.96% MIT-BIH testing is 95.73%	94.9%	98.37%	96.3%
Testing Database	Clinical trials MIT-BIH	Open source	Open source	Open source

4. CONCLUSION

In order to improve health, this study suggests a full AIoT system platform that is an integrated health-care system that includes hardware, software, and a cloud database. In comparison to other algorithms, the AI-based method for arrhythmia classification, which uses expert cardiologist advice as a guide, has a simpler data pre-processing progress and an appropriate identification pattern. However, more data from various clinical patients are required, which can be utilized to train the model and further alter the pre-processing function, in order to overcome the issues caused by individual variances and increase the model's tolerance. Additionally, the measurement used in this study is a single lead ECG; therefore some kinds of arrhythmia cannot be examined. The goal of this effort is to make the model as straightforward as feasible in order to implement AI-based algorithms on a chip in the future. Reaching a true AIoT-based system for heart illness diagnosis and providing universal health care is the goal.

REFERENCES

[1] Top ten causes of death by broad income group (2012). World health organization. Retrieved May, 2014. [Online]. Available: http://www.who.int/mediacentre/factsheets/fs310/en/index.html.

[2] Carlos A Morillo, Amitava Banerjee, Pablo Perel, David Wood, and Xavier Jouven, "Atrial fibrillation: the current epidemic," Journal of Geriatric Cardiology, vol. 14, no. 3, pp.195-203, 2017.

[3] Moody GB, Mark RG, "The impact of the MIT-BIH arrhythmia database," IEEE Engineering in Medicine and Biology Magazine, vol. 20, no. 3, pp.45-50, May/June 2001.

[4] U. R. Acharya, H. Fujita, O. S. Lih, M. Adam, J. H. Tan, C. K. Chua, "Automated detection of coronary artery disease using different durations of ecg segments with convolutional neural network," Knowledge-Based Systems, vol. 132, pp. 62-71, Step. 2017.

[5] U. Desai, R. J. Martis, U. R. Acharya, C. G. Nayak, G. Seshikala, S. K. Ranjan, "Diagnosis of multiclass tachycardia beats using recurrence quantification analysis and ensemble classifiers, " Journal of Mechanics in Medicine and Biology, vol. 16, no. 01, 2016.

[6] U. R. Acharya, H. Fujita, M. Adam, S. L. Oh, J. H. Tan, V. K. Sudarshan, J. E. W. Koh, "Automated characterization of arrhythmias using nonlinear features from tachycardia ECG beats, " IEEEInternational Conference on Systems, Man, and Cybernetics, Oct. 2016, pp. 533-538.