TYPE Original Research
PUBLISHED 14 November 2022
DOI 10.3389/frsc.2022.1073486

ECG diagnosis for arrhythmia detection with a cloud-based service and a wearable sensor network in a smart city environment

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SPECIALTY SECTION
This article was submitted to Smart Technologies and Cities, a section of the journal Frontiers in Sustainable Cities

RECEIVED 18 October 2022
ACCEPTED 31 October 2022
PUBLISHED 14 November 2022

CITATION
Prajitha C, Sridhar KP and Baskar S (2022) ECG diagnosis for arrhythmia detection with a cloud-based service and a wearable sensor network in a smart city environment.
Front. Sustain. Cities 4:1073486.
doi: 10.3389/frsc.2022.1073486

Irregular heartbeats are a primary indicator of Cardiovascular Disease (CVD), which is the leading cause of death in a developing smart city environment. Wearable devices can reliably monitor cardiac beats by producing Electrocardiogram (ECG) readings. The considerable value gained from a wireless wearable system allows for remote ECG assessment with continuous real-time functionality. The data collected from the wearable sensor network in the smart city platform gives timely alarms and treatment that could save lives. Cloud-based ECG methods can be accurate to a certain extent, as latency is still an existing problem. Cloud-based portals linked immediately to wearable devices can provide numerous advantages, such as reduced latency and a good level of service. Therefore, a novel cloud-based arrhythmia detection using the Recurrent Neural Network (RNN) (NC-RNN) method has been proposed for the ECG diagnosis with a wearable sensor in the smart city environment. The ECG signal collected from the wearable sensor involves three phase diagnosis stage. R-peak detection techniques are used for preliminary diagnostics in edge devices. The ECG signals are then classified using RNN at the edge device, with the severity of irregular beat detected in the ECG signal. Finally, a cloud platform classification method can evaluate the obtained ECG signals. While the proposed method's training session is runnable on the technically rich Cloud data centers, the interpretation unit is deployed over the cloud infrastructure for evaluating the ECG signals and setting off the emergency remedies with minimum latency. The simulation results of the suggested framework can accomplish effective ECG detection *via* wearable devices with high accuracy and less latency.

KEYWORDS

Electrocardiogram (ECG), Recurrent Neural Network (RNN), latency, cloud device, Cardiovascular Disease, arrhythmia detection

10.3389/frsc.2022.1073486

Introduction

As the world's population rises, there is a demand for healthcare facilities to accommodate its citizens (Jurcik et al., 2021). The typical lifespan of people in many countries has decreased due to globalization, infant mortality, and plastic pollution (Sharma H. B. et al., 2021). Hazardous air pollution is additionally a leading cause of heart disease in people and animals (Aryal et al., 2021).

The World Health Organization reports a million deaths annually from cardiovascular illnesses (Hall et al., 2021). Although there is no treatment for some of these conditions, they can be managed with regular heart health monitoring and appropriate preventative actions (Watanabe et al., 2021). The health of a person's heart can be evaluated in several ways, including blood tests, ECGs, and stress tests (Bond et al., 2021). Periodic monitoring is best achieved with ECG since it is non-invasive, highly suggestive, and needs minimal complex machines than the others (El-Hajj and Kyriacou, 2021). In a smart city environment, developing smart devices with wearable sensors predict diseases at the earliest stage (Ghazal et al., 2021). The information collected from the wearable sensors in the smart city environment gives an alert message to the doctors, even from remote areas (Sharma et al., 2021).

The primary areas of investigation in the field of telemedicine in healthcare focus on developing reliable and effective methods of remote diagnosis (Ning et al., 2021). The development of a distant location cardiac tracking system for patients is aided by using several Internet of Things (IoT) devices, such as a smart vest and a chest strap, to interpret ECG readings at home (Singh et al., 2021). However, practical analysis of the ECG signals obtained by IoT-based systems is necessary for detecting cardiovascular disorders (Raeesi Vanani and Amirhosseini, 2021). Wearable sensor systems innovation supported by the IoT is a rapidly growing industry in the healthcare sector (De Fazio et al., 2021). Because of the rapid growth of the healthcare industry, a convenient method of in-home diagnostics is allowed for close data monitoring and management (Kumar et al., 2021). The ultimate goal is to incorporate IoT into smart homes, hospitals, electronic health records, etc. (Hossain et al., 2022). Collecting the information in real-time allows doctors at an innovative hospital to track a patient's condition as it develops (Premkumar et al., 2022). This can aid in developing new healthcare, medical, pharmaceutical, and vaccine-related developments (Defendi et al., 2022). The ultimate aim is to ensure data security while allowing authorized users to access it using cloud computing, fog computing, etc. (Deokar et al., 2021).

Patients with a wide range of cardiovascular disorders would benefit greatly from quick ECG analysis and prompt treatment made possible by real-time healthcare technology (Rathi et al., 2021). Modern wireless wearable ECG solutions rely on diagnostic algorithms created for Artificial Intelligence systems through software engineering. Due to the computational complexity involved, they are typically used in an offline, one-dimensional setting (Singh and Pillay, 2022). To pump blood, the heart relies on electric signals to control the contractions of many chambers. The intensity and regularity of heartbeats can be determined by reading these impulses from outside during testing. Smart vests, Fitbits, and chest straps are just some of the IoT gadgets used to read ECG readings in the home environment, with the development of a system for keeping tabs on cardiac patients remotely.

Furthermore, ECG readings acquired from IoT-based systems require precise analysis to diagnose cardiovascular disorders. There have been numerous recent developments in ECG signal processing that center on Edge devices or sensor devices. For instance, wearable devices evaluate ECG signals to identify irregularities like arrhythmia. Such methods often yield accurate ECG analysis results in seconds, and they do so with a high degree of efficiency. On the other hand, while these are fine for everyday use, they may not be up to snuff for more delicate healthcare applications requiring high precision and low latency. Nevertheless, the capacity restrictions of wearable devices mean that systems focused on Edge computing always have constraints.

Since everyone's heartbeats typically exhibit a constant pattern, any deviation from this pattern on an ECG indicates a possible heart problem. ECG readings are recorded and analyzed using complex, laborious computer programs as part of the framework. Flexible ECG diagnosis could benefit significantly from strategically incorporating such approaches in edge devices, eliminating the need for constant contact with cloud databases. Independently diagnosing the ECG signals with high accuracy would conserve transmission power with less delay. Farooq et al. (2021) developed a wearable wireless sensor system. The proposed method presents an innovative, low-cost method for classifying the ECG waveform that may be implemented in the cloud platform. The combined sensor system collects an ECG sensor's input signal, processes it in the cloud platform, and then outputs a classification. In addition to earlier entry to hospital support systems, this setup has the potential to ease congestion in busy emergency rooms in the healthcare field.

Xia et al. (2018) introduced DNN to classify ECG signals. The ECG data is collected using a Bluetooth 4.2-enabled wearable device with wireless sensors and then transmitted to a computer. Then, the automatic cardiac arrhythmia classification system analyses the ECG data and assigns the appropriate categorization with an accuracy of 98%. During the learning phase, the most valuable samples are chosen using a technique that uses the posterior probability associated with confidence measures from deep neural networks.

Ramesh et al. (2021) proposed a deep convolutional neural network (DCNN). A one-dimensional deep convolutional neural network trained with Heart Rate Variability-derived characteristics to categorize heart function from ECG and photoplethysmography (PPG) based sensors into sinus rhythm and atrial fibrillation within 30 s. The experimental result with an accuracy of 95.50%, sensitivity of 94.50%, and specificity of 96.00% is obtained.

Sabbadini et al. (2022) discussed Atrial Fibrillation Detection. To combat Cardiovascular Diseases, a system uses wearable devices in conjunction with deep learning to provide edge technology. The concept is then installed locally on the device and assessed without the requirement for internet connectivity or other devices.

Ksiazczyk et al. (2021) proposed Healthcare Access–Smartphone Apps. A look at the apps for tracking heart rate and identifying arrhythmias is concentrated on assessing accessibility and effectiveness. Initial diagnosis of atrial fibrillation has been shown to reduce stroke incidence and public health costs, and the results indicate that this trend will continue.

Duncker et al. (2021) subjected regarding atrial fibrillation, the real-world applications and developments of such technologies for various arrhythmias, cardiovascular illnesses, and risk indicators for these conditions. Holter monitors, event recorders, ECG patches, wristbands, and textiles are all part of a growing area of wearable technology in cardiology to treat non-atrial fibrillation arrhythmias.

Lee et al. (2022) developed compressed Deep Learning (CDL) method to exploit ECG data and classify arrhythmia in an embedded wearable device. An integrated wearable device is used to apply and evaluate Resnets and Mobilenets with concept compression for detecting arrhythmia. The performance result is in the form of an accuracy of 97.03%.

Umar et al. (2021) proposed Smart Cardiac Care System to bring Cardiac Units with a low-cost, high-accuracy answer that allows for continuous monitoring of patients in a private setting with minimal patient contact from medical staff. A cardiac patient's vital signs must be constantly sampled at varying speeds. This model is one of a kind since it uses a hybrid approach, incorporating both traditional cardiovascular metrics and ECG data.

Jeong et al. (2021) introduced A Real-Time Wearable Physiological Monitoring System. An ECG/EMG signal tracking system uses a wireless physiological information-gathering device and a smartphone-based application framework for real-time data analysis and tracking. Cloud service accessibility is developed in the monitoring system.

Zhang et al. (2021) described Convolution Neural Network (CNN) Over-fitting as a known issue in AF recognition, and this research looked into two possible training ways to combat it. The first involves reducing the impact of diversity by employing the Fast Fourier transform (FFT) and a Hanning-window-based filter. One strategy for making models robust is to use data from wearable ECG devices for training. The accuracy is in the form of 96.23%.

Several problems associated with the delay and classification of arrhythmia are focused on the developed a novel cloud-based arrhythmia detection method. The three stages involve the R-peak identification and classification by RNN. The obtained ECG signals were evaluated by a classification method in cloud services. The interpretation unit is deployed over the cloud infrastructure to evaluate the ECG signals and set off emergency remedies with minimum latency.

A novel cloud-based arrhythmia detection

There are five main computer components in the proposed model of specific devices, gateway, and cloud technology for dynamic ECG diagnosis. Between specific devices, Personal Digital Assistants (PDA) (Edge device), and remote cloud storage, there are two additional elements: fog devices and center. From specific devices to remote systems, computational power and resources increase steadily. As a result, the problem's computational complexity at any given time affects how an adaptive ECG diagnosis allocates its resources. The architecture of NC-RNN in a smart city environment is shown in Figure 1.

The Fog Device is a cloud storage center; it collects physiological data from wearable devices. The data collected is given to PDA, which is also called an edge device. Health records store the collected data in the cloud for future verification. The center devices represent the Fog Device, cloud device, and health records. The complete architecture of Figure 1. is based on the smart city environment. The healthcare implementation is completely utilized in the smart city platform. The health records are stored for future benefits in the smart city environment.

Specific devices

The digital gadget used in the proposed section is wearable devices, and IoT devices include PDAs. The wearable sensor collects the physiological data from the patients, and the data is given to PDA. If any irregular heartbeat is detected, the alarm is given so the health care professionals can take care of any serious patient condition. Any digital gadget with built-in ECG sensors that tracks the patient's heart rate and rhythm in actual time is considered a specific device. An NC-RNN proposes a wearable sensor that continuously monitors the patient's heart rate *via* an incorporated R-peak detection algorithm. If an irregular heartbeat (arrhythmia) is discovered, the data is transferred to a nearby inference unit for additional analysis. Despite the

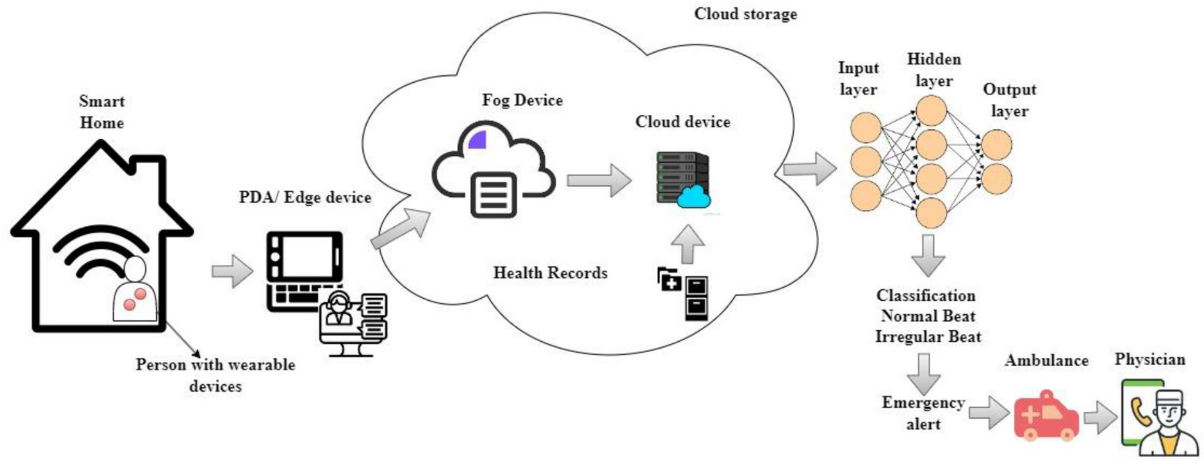

FIGURE 1
Architecture of NC-RNN in a smart city environment.

decreased efficiency of regional categorization relative to edge and cloud servers, it improves the R-peak detection technique. If there's nothing out of the ordinary, the specific device goes into a power-saving standby mode. The R-Peak detection algorithm is based on the Discrete Wavelet Transforms (DWT) to identify the local device's first signs of an anomaly. Because of its superior processing of the actual ECG signal, DWT is employed for R-peak detection. R-peak detection by DWT is shown in Equation (1).

$$y(m) = (a * s)(m)\ \Sigma_{r=-\infty}^{\infty}\ a(r)\ s(m-r) \tag{1}$$

From the above Equation, m denotes the number of samples, a denotes the input ECG signal, r represents the number of devices in the cloud platform, s represents the actual ECG. The noise in ECG signals leads to false detection and diagnosis of arrhythmia, so for accurate detection, the noise from the collected ECG signal must be reduced. The most important types of noise in ECG signals are powerline interference, high-frequency noise, baseline wander, and noise due to muscle movement. The filters remove all such types of noises from the ECG signal. The SNR comparison is made with the noise detection stage. The SNR of the proposed method depends mainly on the noise reduction stage of the high and low pass filters. The noise in the ECG signal needs to be considered for better diagnosis and classification of arrhythmia. The obtained signal is given to a low pass and high pass filter, as shown in Equation (2), to reduce the ECG signal's noise.

$$\left.\begin{array}{l} y_L(m) = \sum_{r=-\infty}^{\infty} a(r)\ s(2m-r) \\ y_H(m) = \sum_{r=-\infty}^{\infty} a(r)\ t(2m-r) \end{array}\right\} \tag{2}$$

$y_L\ (m)$ represent the low-pass filtering stage, $y_H\ (m)$ denote the high pass filtering stage. Local Devices use a few steps to Track ECG signals.

- The wearable sensors track ECG signal $e(s)$ as input data.
- Identifying an irregular heart rate and R-R interval is represented as an output data.
- Discrete wavelet transform is used for R-Peak detection.
- From obtained R-peak wave, low-pass and high pass filter is used to remove the noise from signal.
- Heartbeat needs to be computed by identifying the R-peak.

DWT is used for R-Peak detection. The implementation of DWT obtains the spectrogram analysis of the collected and noise-reduced ECG signal. Once the specific device R-peak detection algorithm has identified abnormal ECG signals, clear device ECG signals are sent to the PDA for additional examination. Before this happens, the particular device should search for back-to-back irregularities in the patient to determine if there is an actual healthcare problem. A formula for determining a person's typical heart rate in beats per minute is shown in Equation (3).

$$\frac{total\ number\ of\ R-peaks\ \times 60}{duration\ between\ R-peaks} \tag{3}$$

The time required for a specific device to evaluate an ECG signal of pattern length M with S_r is the amount of ECG sample treated per second by the R-peak detection stages. The input ECG signal is illustrated in Figure 2A, and the noise-removed signal is illustrated in Figure 2B; the detection of R-peak is illustrated in Figure 2C.

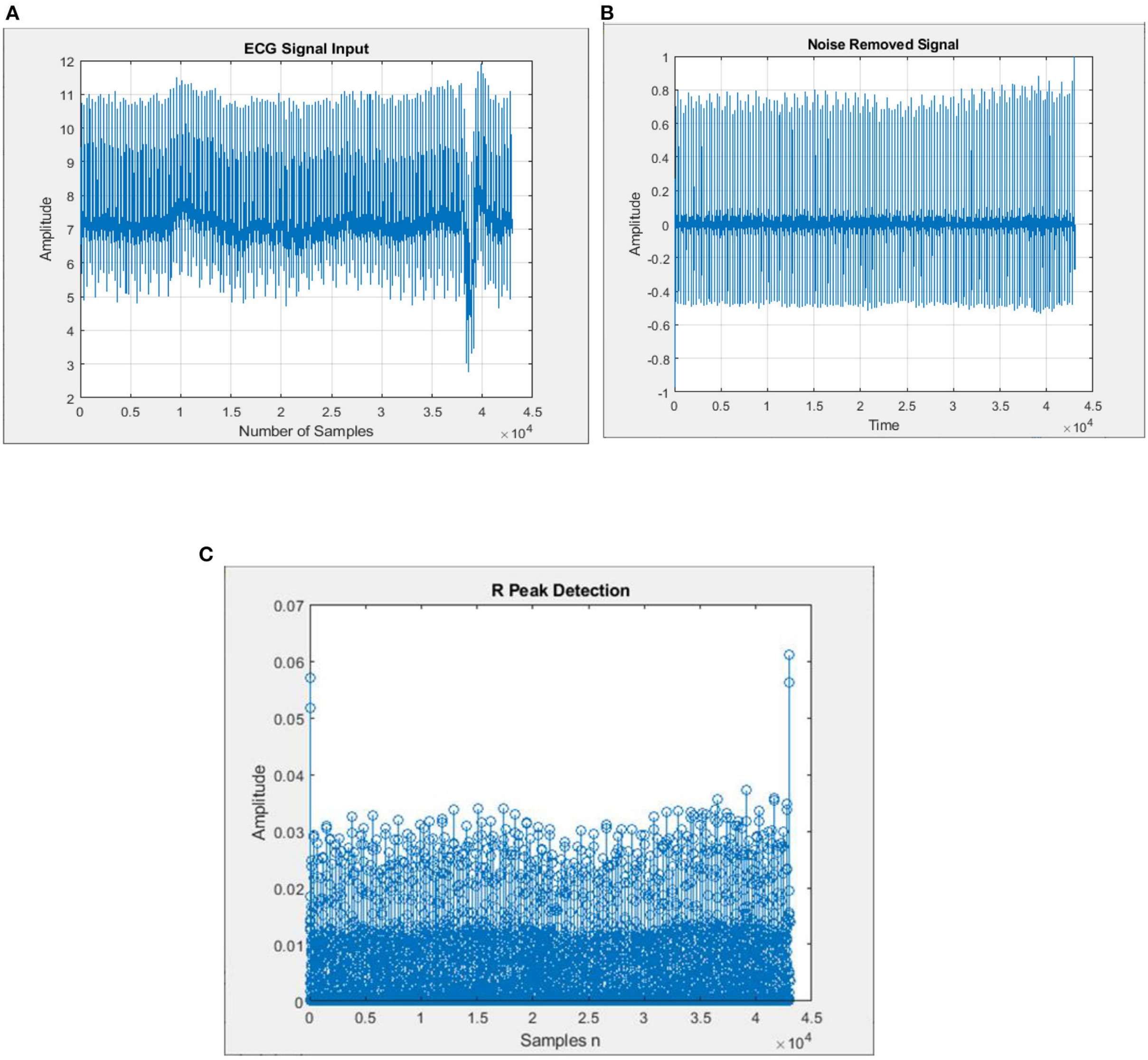

FIGURE 2
(A) ECG signal input. **(B)** Noise removed signal. **(C)** R-peak detection.

PDA

PDAs are considered the edge devices like smartphones. Smartphones have more computational power than their local counterparts. A spectrogram is a two-dimensional representation of ECG generated by a discrete wavelet transform. RNN is used to categorize the Spectrogram. PDA will identify if the ECG signals are of a standard or abnormal rhythm. When an edge device detects something out of the ordinary, it immediately notifies the central server in the cloud and fog. After the noise reduction stage, the discrete wavelet transform is used to find the Spectrogram of the ECG signal. RNN classifies the obtained Spectrogram. The smart city platform achieves arrhythmia diagnosis and classification depending on the regular and irregular heartbeat. The steps for the Evaluation of PDA are as follow:

- Collect ECG data in frames from a nearby monitor $e(s)$ that can be given as input.
- Categorization of Arrhythmias and normal sinus rhythms is obtained as output.
- Estimation of Spectrogram by discrete wavelet transform.

- The optimum value of the discrete wavelet transform constants is then used to turn each screen of ECG signals into a spectrogram.
- RNN is used to categorize Spectrograms for precise ECG analysis.
- Send the findings of the categorization to the cloud or the healthcare servers.

The individuals are monitored, and the ECG signal collected from the person in the smart home environment is a Fog device. The data collected from the gateway is stored in the cloud for future use. The data collected from the smart home environment is given to the PDA if abnormalities are seen. An alarm is given to the doctor in the healthcare environment, illustrated in Figure 3.

Fog devices

Fog device elements exist in the network among PDA and the cloud. Fog servers can be anything that improves cloud server connectivity. Fog devices are closer to the users; therefore, they can offer more computational power than the PDA. If more training data and better parameters were available, the RNN classification might achieve higher accuracy. In addition, intermittent cloud connectivity may enhance power usage and cause fewer delays. The power usage of clouds detects the delay of the data in the form of each patient's health records. Therefore, the classification findings and ECG signals should be transmitted from PDA to fog servers. When communication issues are present in an edge-cloud system, fog devices may be employed instead of the cloud.

Sending an ECG signal from a specific device, PDA, or fog device to these computers allows further processing and evaluation. Systems in the cloud provide the most processing power available. After transmission, the data is processed and categorized using RNN to ensure the maximum possible precision. If the healthcare server needs access to more information about a patient, the server sends a request to the periphery equipment to gather that data. A cloud server, for instance, might ask PDA to provide it with a specific frame of an ECG signal. The collected signal from the wearable sensor is pre-processed and given to the edge device; PDA is a fig server. The data is stored in the cloud server, as illustrated in Figure 4.

Wearable ECG sensors are used to collect information on ECG signals from individuals. The proposed concept includes a gateway to handle the increased data traffic from multiple nearby patients. Due to communications and bandwidth limitations, organizing massive amounts of patient data is essential. The gateway connects various PDA and cloud nodes to the cloud and fog servers. If the R-peak detection algorithm discovers an irregular ECG, the offending frames would be transmitted with less latency, as shown in Equation (4).

$$e(mS) = [a(m_1S),\ a(m_2S)\ldots\ldots\ldots a(m_yS)] \tag{4}$$

S represents the sampling rate of the collected ECG signal, and N denotes the length of the samples. When a PDA obtains an irregular ECG signal, the discrete wavelet transform of each frame is determined by the steps below:

$$B\left(x,y\right) = \frac{1}{\sqrt{x}} \int \frac{e(s)\varnothing^*(s-y)}{x} dt \tag{5}$$

$e\,(s)$ is the time at which the ECG signal is irregular. x and y are scaling and translational factors and $\varnothing$ is the transfer function. The irregular ECG signal is represented on the timeframe by the function $B\left(x,y\right)$.

The relation between Equations (1) and (5) is the same as the discrete wavelet transform for determining the irregular heartbeat and R-peak detection. The R-peak detection algorithm can be offended as a frame with less latency.

The proposed system separates the PDA and cloud platform by a fog device. A fog device positioned at a small range could conduct an in-depth evaluation of ECG signals if it is projected that the interconnection between the PDA and the cloud server would cause delays in the operation. Let S_M represent the duration it takes for the patient's ECG data to travel from the PDA to the healthcare provider's server.

The duration it takes for the patient's ECG data to go from the PDA to the fog device is given as S_P. Data evaluation is implemented at the Fog layer in this structure for a distant patient monitoring system. When an ECG signal is received, an interpretation unit analyses it to determine its type and whether or not the patient has any abnormalities. Thus, the system's reaction rate is improved by providing instantaneous feedback. In addition, once the interpretation component has identified an activity of significance, the appropriate instruction is communicated to the sensor layer to activate emergency services while keeping an eye on whether or not this is necessary. After that, the sensor layer sends the ECG signals, the activation instruction, and the response to the central cloud so that the training schedule can be consistently upgraded.

The central gateway in the cloud acts as the foundation for the proposed health monitoring system. It takes in ECG signals from the Fog layer, processes them, and records the resulting answers and service results in a universal database for easy access from anywhere in the world. ECG monitoring and issue identification use different situations in the system's implementation and evaluation. The findings demonstrated the system's potential for high accuracy, which could contribute to enhanced healthcare delivery. The entire flow diagram of the proposed NC-RNN is shown in Figure 5. The initial step is data collection, followed by pre-processing, which includes noise reduction. R-peak is detected for ECG signal. RNN classifies peak detected signal as regular and irregular beat.

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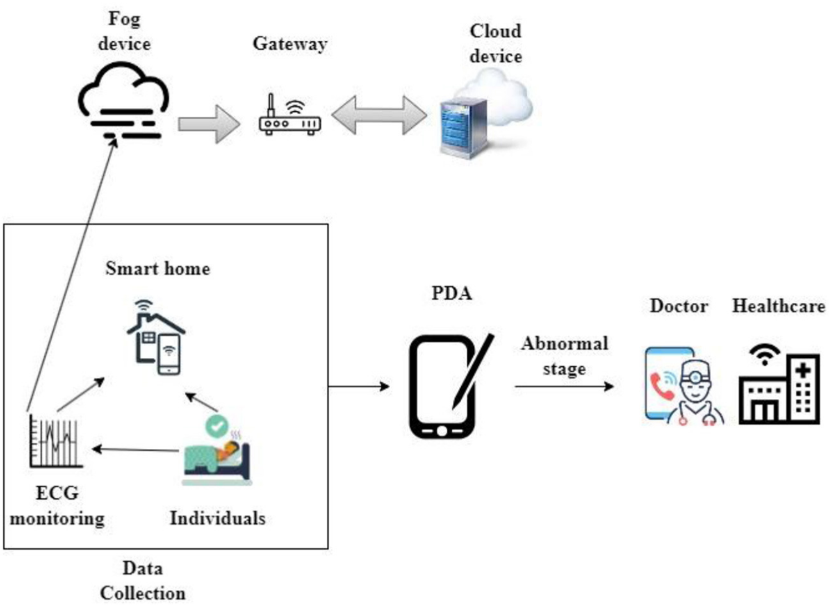

FIGURE 3
Data collected from smart home environment.

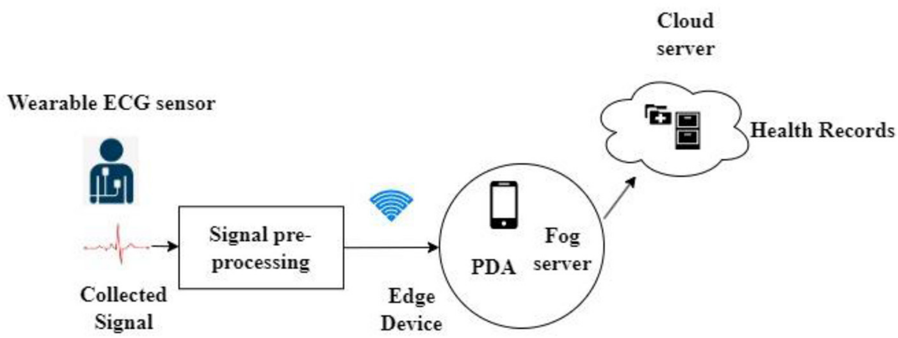

FIGURE 4
The stages of data collection.

Result and discussion

The proposed method was evaluated using samples from the MIT-BIH dataset[1]. There are 48 recordings, and each one records two-lead ECG signals from 47 people for about 30 min. Band-pass filtering occurs between 0.1 and 100 Hz, and 360 Hz samples are used to record the resulting ECG signals. Labeling for timing and rhythm class data has been included in this database, and external experts have verified it. The evaluation parameters are in the form of accuracy, sensitivity, specificity, latency, and SNR. The accuracy of NCC-RNN is obtained by using Equation (6). The accuracy of a binary classification test is measured statistically by how well it confirms or rules out a diagnosis in arrhythmia detection. Accuracy (A) measures how many cases of a given number were correctly predicted in the classification of normal or irregular heartbeat for arrhythmia, illustrated in Figure 6.

$$A = \frac{tp+tn}{tp+tn+fp+fn} \tag{6}$$

From the above Equation, tp represents the true positive, tn denote the true negative, fp represents the false positive, fn denote the false negative.

A diagnostic tool's sensitivity (S) is defined as its capacity to identify individuals with irregular ECG beats. Sensitivity, or

1 https://www.physionet.org/content/mitdb/1.0.0/

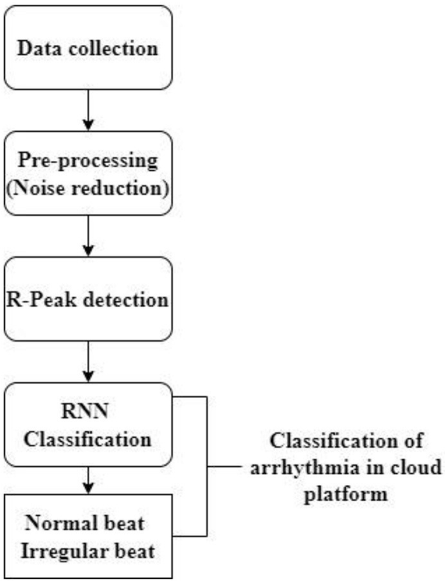

FIGURE 5
Flow diagram of NC-RNN.

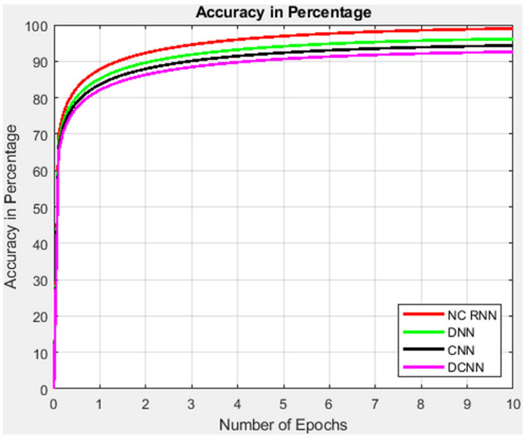

FIGURE 6
Accuracy of NC-RNN.

detection rate in a clinical environment, refers to the percentage of individuals who test positive for a disease (irregular heartbeat) or condition compared to the total number of people who have that disease. The sensitivity is calculated using Equation (7), shown in Figure 7.

$$S = \frac{tp}{tp+fn} \tag{7}$$

In Sensitivity *tp* represent the true positive, *fn* denote the false negative.

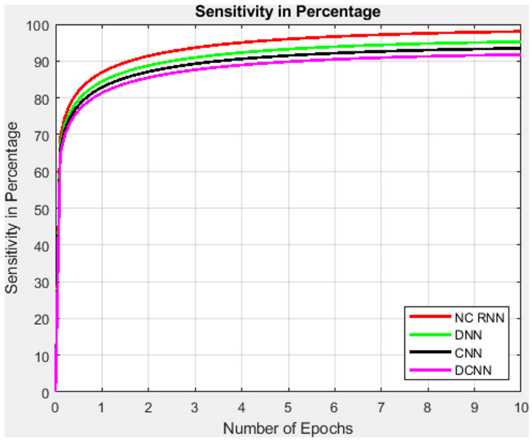

FIGURE 7
Sensitivity of NC-RNN.

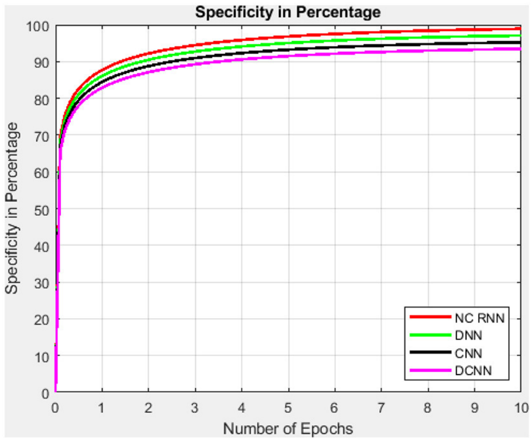

FIGURE 8
Specificity of NC-RNN.

The specificity (sp), in particular, depends on how well it can rule out abnormal results in healthy people. The specificity of a test is defined as the percentage of people who tested negative for an irregular heartbeat who do not have arrhythmia disease. The specificity is calculated using Equation (8), shown in Figure 8.

$$sp = \frac{tn}{tn+fp} \tag{8}$$

Precision (P) is the proportion of relevant instances that were accurate, and it is shown in Equation (9).

$$P = \frac{tp}{tp+fp} \tag{9}$$

The precision of the proposed NC RNN is shown in the Table 1.

The SNR measures how much information can be retrieved from an ECG signal by subtracting the noise level. This is

TABLE 1 Precision of NC-RNN.

Epochs	DNN	DCNN	CNN	NC-RNN
1	98	96.78	98.01	96.67
2	96.21	97	97.34	97.21
3	97.04	94.33	97.89	97
4	92.10	91.21	96.65	98
5	93.23	90.36	92.10	98.12
6	95.67	94.67	90.21	97.66
7	93.21	97.57	92.56	98.01
8	90.98	90.33	97.65	98.48
9	91.23	94.77	96.66	97.45
10	90.89	97.8	95.1	96.78

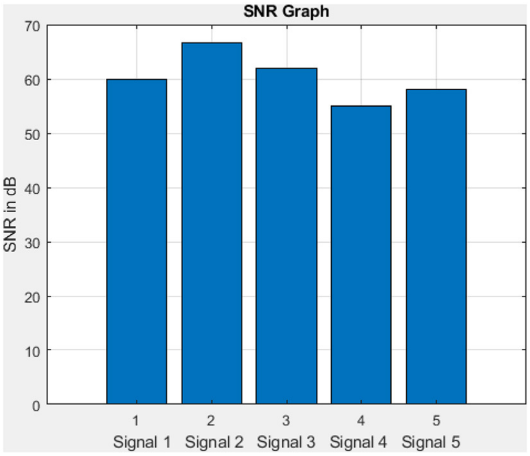

FIGURE 9
SNR of NC-RNN.

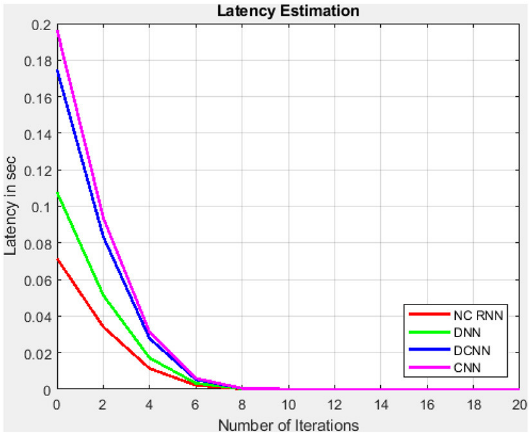

FIGURE 10
Latency of NC-RNN.

because electrode noise, motion artifact, and other such factors frequently impact the obtained ECG signal, which delays the identification procedure and reduces the quality of disease forecasting. Pre-processing the signal before compression helps eliminate the noise signals without compromising the accuracy of the data. The SNR Comparision of signals is shown in Figure 9.

The specific and PDA are simultaneously used in the proposed NC-RNN, and the amount of unhealthy data in the network is significantly decreased. The total amount of data traffic consequently dropped drastically. In addition, there is less potential for lost information. A signal experiences a delay as it travels between all the cloud storage devices. The latency is less in the proposed method, as obtained from Equation (4), shown in Figure 10.

The proposed NC-RNN is compared with Convolution Neural Network (CNN), deep convolutional neural network (DCNN), and Deep Neural Network (DNN) in the form of accuracy, latency, SNR, Sensitivity.

Conclusion

Electrocardiogram (ECG) readings can be successfully generated by wearable devices, allowing for constant monitoring of heart rates. A wireless wearable system is extremely useful since it enables remote ECG assessment with stable real-time functionality. Wearable sensors in the smart city platform collect data that can be used to trigger lifesaving alarms and interventions. Although cloud-based ECG algorithms have improved, there is still a latency issue. Using cloud-based portals with direct connections to wearable devices has many potential benefits, including lower latency and higher quality of service. NC-RNN is implemented for ECG diagnosis using a wearable sensor in a smart city setting. Three diagnostic stages exist for interpreting the ECG signal from the on-body sensor. Initial diagnostics in edge devices detect the R-peak detection. An RNN classifies the ECG signals at the edge device according to the observed irregular beat's severity. The suggested method's training session can be executed in the feature-rich Cloud data centers, and the interpretation unit is implemented in the cloud to analyze ECG signals quickly.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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