# Remote Healthcare Monitoring System for Aging Population Based on IoT and Big Data Analysis

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***Abstract*—As the population ages, this will put tremendous pressure on pensions and the medical system. Health insurance for the elderly poses a major challenge to the allocation of limited medical resources. The Internet of Things (IoT) is widely regarded as a potential solution to relieve pressure on healthcare systems. With the rapid development of wireless communication technologies such as backscatter communication, Wi-Fi and 5G, in vivo and in vitro medical devices have been greatly developed. In this article, we propose a real-time big data healthcare analysis system based on the combination of shallow neural networks and deep neural networks. The system consists of two parts: the detection of fog layer abnormality based on shallow neural network and the diagnosis of cloud disease based on deep neural network. The system can not only make full use of the real-time nature of the fog layer but also give full play to its powerful computing power based on reducing the computing pressure of the cloud layer.**

***Keywords—Internet of Things (IoT), big data, healthcare, fog-cloud computing, artificial neural network (ANN)***

## I. Introduction

As the population ages, the healthcare system will face tremendous pressure [1]. The health threats of older people are mainly concentrated in chronic diseases such as high blood pressure, heart disease, stroke, diabetes, cancer and respiratory diseases [2]. With the increase of the elderly population, the number of chronic diseases will inevitably increase, which poses a huge challenge to the allocation of limited medical resources. The Internet of Things (IoT) is widely regarded as a potential solution to relieve pressure on healthcare systems [3].

With the development of cloud computing [4], fog computing [5], artificial intelligence [6] and the Internet of Things, medical systems based on big data analysis have greatly developed. Healthcare systems based on big data analysis can be used to analyze abnormalities of different vital signs, such as electrocardiogram, electromyogram, temperature, blood pressure, blood glucose and other information. By analyzing the abnormalities, the possibility of disease can be predicted, the workload of medical staff is reduced, and the pressure on the healthcare system is effectively reduced.

Healthcare systems based on big data analytics require large amounts of data collected by IoT devices or sensors, and then analyze and make decisions in the cloud layer or the fog layer. However, the real-time transmission of data from IoT devices or sensors remains a huge challenge. If an IoT device communicates wirelessly by actively generating a signal, it consumes a lot of energy. For example, an in-body implant such as a wireless capsule used in endoscopic inspection consumes twice as much energy for data transmission as the sensor perceives an image [7]. On the other hand, limited battery capacity will limit the effective working time of the device, and increasing the capacity of the capsule battery will increase the volume of the capsule space, which will undoubtedly increase the difficulty of swallowing [8]. The device size and battery capacity will undoubtedly be one of the key factors for the widespread popularity of in-body implants and on-body sensors. Therefore, new solutions for real-time data transmission of in-body implants and on-body sensors have become important research directions for the development of healthcare systems.

Backscatter communication is an emerging passive communication technology that can effectively solve sensor network communication and energy efficiency issues, and is expected to become an effective data transmission solution for low power IoT applications [9]. Backscatter communication can be widely used in low-power consumption scenarios such as embedded devices, industrial Internet of Things, connected houses, and wearable devices, which can effectively solve the communication problem between devices. In fact, the potential benefits of backscatter communication will greatly affect the mode of interaction between doctors and patients and the way healthcare data is transmitted in healthcare systems [10].

In this paper, we propose a real-time big data healthcare analysis system based on ambient backscatter communication. This system consists of two parts, namely a real-time big data healthcare analysis system based on artificial intelligence and a real-time data transmission system based on ambient backscatter communication. The real-time big data medical analysis system is the core of monitoring and diagnosing the user's health, while the real-time data transmission system provides a powerful data transmission guarantee for the real-time big data medical analysis system.

The real-time big data healthcare analysis system is based on the combination of shallow neural networks and deep neural networks to monitor and diagnose the user's health state. The system mainly includes three layers: a data acquisition layer, a fog layer, and a cloud layer. The data acquisition layer consists of sensors, IoT devices, and medical data. Depending on the type of data, the collected information is transmitted to the fog layer or the cloud layer through different data transmission networks. The fog computing layer performs anomaly detection based on specific tasks by using shallow neural networks. The cloud layer performs deep neural network learning based on the anomaly report and the collected related data uploaded by the fog layer, and gives the main reasons for the anomaly and the corresponding disease response measures. The introduction of the fog layer has greatly reduced the computational pressure of the cloud layer and the pressure of data transmission in the core network.

## II. System Model

The framework of proposed system is shown in Fig. 1, which is used to monitor the healthcare of users in real-time. The system consists of three layers in terms of data acquisition layer, fog layer and cloud layer. The data acquisition layer consists of various IoT devices and sensors to efficiently capture health-related data of users. Then the accumulated data is transmitted to the fog layer for real-time monitoring through wired or wireless transmission protocols. After the fog layer diagnoses the disease, it immediately sends an alarm message to the user and takes preventive measures in time. At the same time, each user's analysis results and aggregated medical information are stored on the cloud for subsequent analysis. The cloud layer regularly analyzes the stored medical information and sends the results to the fog layer for real-time healthcare monitoring.

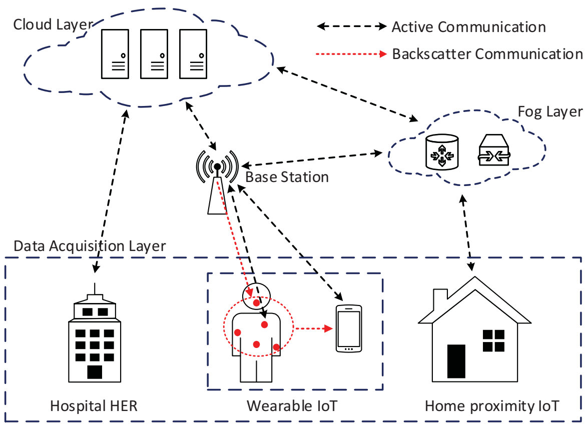


Fig. 1. The real-time big data healthcare analysis system based on backscatter communication and active communication.

### A. Data acquisition layer

The data acquisition layer is the foundation of the real-time healthcare big data analysis system. This layer collects data from different heterogeneous data sources, which typically include things like proximity IoT devices in elderly households, wearable IoT devices for elderly, electronic health records (EHR) for elderly in hospitals, and electronic questionnaires on user terminals devices like tablets or phones. Proximity IoT devices are located in the home of the elderly, mainly collecting environmental information, such as temperature, noise, air quality, and also includes the recent weight and height of the elderly. Wearable devices include in-body implanted devices and on-body sensors that collect the physical state information of the elderly in real-time, such as blood pressure, blood glucose, blood oxygen, heart rate, and exercise status. EHR data usually includes the patient's medical history and various medical information, such as diagnosis, laboratory tests, drugs, image data, etc. Electronic questionnaires are used to register the types of diseases to be monitored and diagnosed and to regularly survey users about lifestyle habits such as drinking and smoking.

### B. The fog layer

The fog layer is a bridge connecting the data acquisition layer and the cloud layer and is the key layer for real-time disease monitoring. It is used to process and analyze the data transmitted from the data acquisition layer in real-time. When anomalies are found, the fog layer will collect detailed data about the anomalies, clean them and send them to the cloud layer for further analysis. Therefore, the fog layer in this paper has three main tasks, data cleaning, anomaly detection, and alarm generation.

*1) Data cleaning:* The fog layer collects physiological data, motion data, environmental data, and historical medical information from the data collection layer. During the transmission process, some data may be missing or redundant due to trans- mission link disturbances. Therefore, it is necessary to identify and delete incomplete and redundant information from the collected data, and replace the missing data with reasonable values. Secondly, different data sources are different, there may be multiple formats, these heterogeneous data need to be converted into a unified format in the fog layer for further analysis.

*2) Anomaly detection:* Anomaly detection is the core of the real-time health monitoring of the fog layer. Traditional anomaly detection mechanisms are based on thresholds. For example, in the identification of cardiovascular disease, the stage of hypertension is usually one of the reference information, which is based on the thresholds of the two attributes of blood pressure, SBP and DBP. The blood pressure classification is obtained in a special environment such as a hospital or a clinic. However, users may be in different motion and physiological states in a non-hospital environment. The blood pressure obtained at this time may be very different from that obtained in a hospital. Therefore, there is a big mistake in judging whether a user has a cardiovascular disease attack based only on SBP and DBP without considering the influence of other factors. Therefore, it is necessary to use artificial intelligence algorithms based on various health data (such as the user's physiological state, activity state, and hospital diagnosis and treatment history information) in the fog layer to detect the user's health abnormalities in real-time. However, the computing power of the fog layer is limited, so when performing anomaly detection, we only consider whether the user is being attacked by a certain disease, regardless of the specific type of the disease, and the cause of the disease. For example, when testing for cardiovascular disease, only the user is considered to have cardiovascular disease without considering the specific classification of cardiovascular dis- ease, such as coronary artery disease, congenital heart disease, valvular disease, and arrhythmia. Studies have shown that detecting only large classes without subdividing small classes can effectively reduce computational complexity and improve accuracy. Therefore, it is a very good choice to use shallow neural network to detect anomalies in the fog layer, which can reduce the computational complexity and have a better calculation accuracy.

*3) Alarm generation:* When anomaly detection detects that the user is being attacked by a disease, an alarm message is generated. At the same time, the fog layer will collect more detailed user health-related data from the data collection layer based on the alarm information, user registration information and hospital diagnosis and treatment records. After cleaning, it will be transmitted to the cloud layer for deeper analysis. For example, during cardiovascular disease abnormality detection based on blood pressure, an abnormality is detected in the fog layer. In order to determine the type and cause of the disease, more detailed ECG information needs to be collected by the data acquisition layer for deep analysis in the cloud.

### *C. The Cloud layer*

The cloud layer is the core of the entire real-time health diagnosis. The main task is to perform in-depth analysis on the data uploaded by the fog layer, make decisions based on the analysis results, and store these data. The alarm information generated by the fog layer and detailed user health data collected are transmitted to the cloud layer. According to the alarm information, the cloud layer uses the deep learning method to analyze the user's disease type in detail. For example, [11] developed a deep neural network to classify and predict the 10 arrhythmias and sinus rhythm and noise in single-lead ECG signals, and achieved better classification accuracy than cardiologists. The cloud layer makes decisions based on the analysis results, notifying users to take necessary first aid measures, medication recommendations, and prevention recommendations. Finally, the cloud layer stores alarm information, user health-related data and analysis results, and edits each user's medical information to be shared among authorized medical personnel, users, pharmacies, hospitals, and medical professionals in order to better serve users.

### *D. Data transfer network*

Multi-protocol data communication needs to be enabled between sensors and between gateways, networks and data centers. A data transmission system that combines backscatter communication and active communication[12][13] (5G, ZigBee, Wi-Fi, 4G, and wired networks) can effectively ensure data transmission and improve system stability and reliability. Backscatter communication is suitable for low-rate data transmission. There are many advantages, e.g., reduction in the size of device, increasing the comfort of wearing, and greatly improving the battery life. Second, due to the reliability and stability of the data transmission, active communication can carry out high-speed data transmission.

*1) Backscatter communication:* User-centered backscatter communication has the potential to increase the service life of wearable devices and human sensors without affecting the physical size of individual devices. Its low-power architecture can not only capture sensor data, but also transmit data within a few meters. The backscatter communication system can adjust hardware and radio frequency according to the requirements of different scenarios to meet different transmission coverage. By effectively exchanging data with a low-power budget, it can completely change the way that medical services are provided through embedded and wearable devices. Due to its low power consumption, it can only transmit low-rate data such as blood pressure, temperature, moderation, and heart rate.

*2) Active communication:* Active communication mainly includes 5G, ZigBee, Wi-Fi, 4G and wired network and other communication technologies. Active communication can transmit high-speed data transmission such as electrocardiogram and electroencephalogram. Its advantage is that the data transmission is reliable and stable. Therefore, a suitable active communication technology can be selected according to different data transmission application scenarios.

## III. HYBRID NEURAL NETWORK ARCHITECTURE

With the improvement of medical level, IoT medical system based on cloud computing has become a trend. Cloud-based IoT healthcare systems store data captured by IoT sensors for calculation and further analysis. However, with the emergence of many new requirements for IoT healthcare systems, cloud computing is facing more and more challenges. For example, cloud computing has poor real-time performance. Massive medical data needs to be uploaded to the cloud, and the core network is under great pressure. Fog computing can provide users with closer computing services, making real-time analysis and decision-making more feasible and effective. In addition, fog computing enables IoT healthcare systems to provide computing, storage, and control services to meet various medical needs. However, the power of fog computing is limited, and cannot meet the computational requirements of deep neural networks with tens or even hundreds of millions of parameter scales. Considering these facts, we propose a medical framework that combines cloud computing and fog computing to identify and control disease onset at an early stage. In other words, we will arrange a shallow neural network at the fog end for anomaly detection and build a deep neural network in the cloud to further determine the type of disease, as shown in Fig. 2.

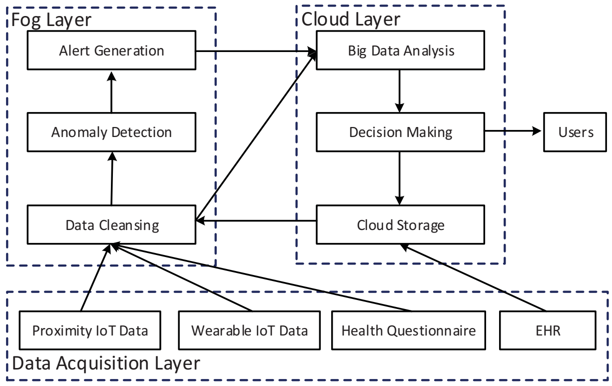


Fig. 2. The real-time big data healthcare analysis system.

In this way, we can not only use the real-time characteristics of fog computing to monitor diseases in real time, but also use the powerful computing power of the cloud to classify diseases in detail. In this article, we mainly predict the attack of heart disease. Since heart disease is a type of cardiovascular disease, we can first determine whether there is a risk of cardiovascular disease outbreak in the fog layer. If users are at risk, we will collect more detailed ECG information for in-depth analysis in the clouds and determine whether users will be at risk of a heart attack.

### A. Shallow neural network based on fog layer

Due to the complex causes of cardiovascular diseases, such as drinking, exercise, stress, anxiety, heart disease patients may face the risk of sudden death. Therefore, it is necessary to design a prediction system to predict (with or without) the risk state of cardiovascular disease onset and protect users from sudden death. The shallow neural network proposed in the fog layer uses a fully connected artificial neural network (ANN) [14]. It judges the risk status of cardiovascular disease attacks by considering the attributes related to cardiovascular disease, such as systolic blood pressure, diastolic blood pressure, cholesterol, alcohol intake, activity status, etc. The backpropagation method is an effective method for training multi-layer artificial heart neural networks. The main goal is to train the network to strike a balance between the network's ability to respond accurately and a better response to input.

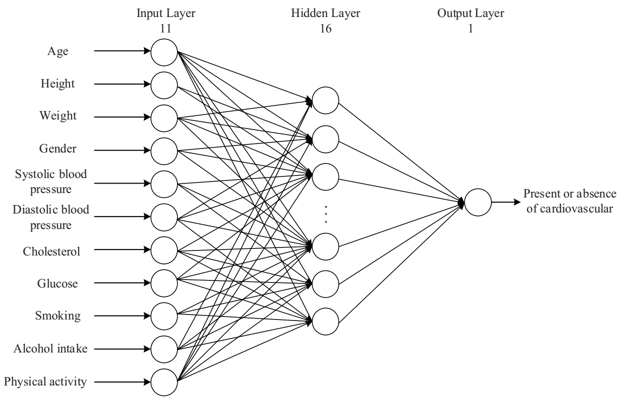


Fig. 3. The fully connected artificial neural network (ANN).

Fig. 3 shows the fully connected feedforward ANN, which has 11 inputs, 16 neurons in the hidden layer and 1 output node in the output layer. There are three main types of input data here: 1) Physical health characteristics that may cause cardiovascular disease, such as systolic blood pressure, diastolic blood pressure, cholesterol level and glucose level; 2) User habits such as smoking, alcohol intake, and physical activity; 3) Basic user information, such as age, weight, height and gender.

When the ANN network detects that the user is at risk of being attacked by cardiovascular disease, it will generate an abnormal alert. Vital signals (signals within a certain period of time before and after the occurrence of abnormal alarms) based on different disease types will be sent to the cloud for further analysis. In this article, we monitor whether the user has been attacked by heart disease, so the user's current ECG data will be transmitted to the cloud for in-depth detection.

### B. Deep neural network based on cloud layer

When the fog layer detects that the user is at risk of being attacked by cardiovascular disease, the cloud layer will collect the user's current ECG information for in-depth analysis. In cloud, deep convolutional neural networks are mainly used for types of heart attacks. The deep convolutional neural network is based on the residual network [15]. The structure of the residual block is as shown in Fig. 4.

As shown in Fig. 4, $x$ is the shallow output, $F(x) + x$ is the is the deep output, and $F(x)$ is the intermediate layer result. When the feature represented by $x$ has reached a good level, the continued learning of the middle layer will lead to an increase in loss, $F(x)$ will slowly approach 0, and $x$ will continue to propagate down from the short cut path. In this way, when the shallow features are good, the deep network behind can achieve an identity transformation effect.

The use of the residual block can effectively train the deep neural network to prevent the network from overfitting. For example, [11] proposed a 34-layer convolutional neural network (CNN), which can detect arrhythmia in ECG time series and achieve good detection results.

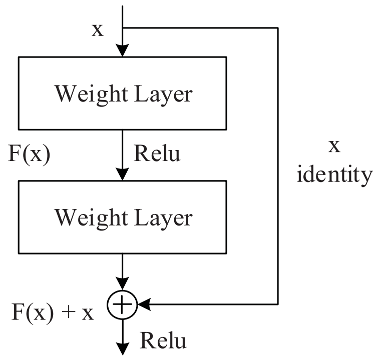


Fig. 4. The basic residual unit.

## IV. SIMULATION STUDY

In the simulation part, we mainly analyze the abnormal detection of cardiovascular diseases based on the shallow neural network in the fog layer as shown in Fig. 3, and the heart disease analysis system based on the deep neural network in the cloud layer can use the existing neural network, such as the neural network proposed by [11].

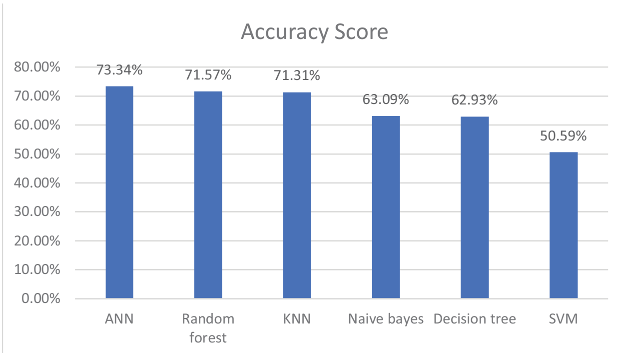


Fig. 5. Accuracy of different machine learning.

We use the cardiovascular disease set published by Kaggle as the data set for the fog layer abnormality detection based on shallow neural networks. The data set contains 70,000 patient data records, which contain 11 health-related features, such as systolic blood pressure, diastolic blood pressure, cholesterol level, glucose level, smoking, alcohol intake, and physical activity, age, weight, height, gender, and a disease label, i.e. presence or absence of cardiovascular disease. We use 80% of the data as the training set and 20% of the data as the test set. The performance of different machine learning methods is shown in Fig. 5. The fully connected ANN structure used in this paper is shown in Fig. 3. It can be seen that the accuracy of the ANN network with 16 hidden layers is 73.34%, which is superior to other machine learning algorithms. Since the proposed ANN architecture has only 16 hidden units, its computational complexity is very low, and real-time monitoring can be achieved. The loss function curve is shown in Fig. 6. Obviously, the loss function shows a downward trend with the increase of the epoch, and eventually remains basically unchanged.

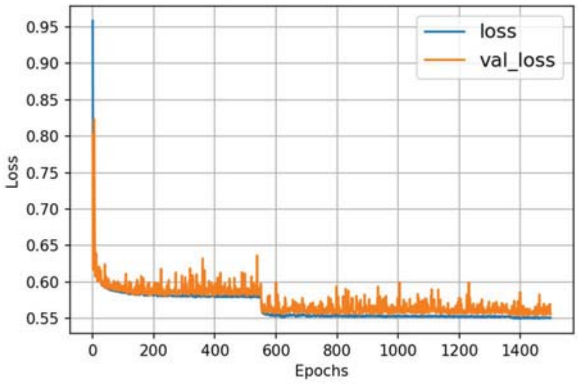


Fig. 6. The loss function curve.

In the anomaly detection of the fog layer, we are more concerned about whether the anomaly can be detected, so we need to study the confusion matrix of the experiment. The confusion matrix is a table consisting of false positives (FP), false negatives (FN), true positives (TP), and true negatives (TN).

In the study of abnormal detection, we are more concerned about whether the abnormal can be detected, rather than paying special attention to the case of detecting normality as an anomaly. Therefore, in the confusion matrix, we are more concerned about TP and FN than FP and TN. Even if a person in a healthy state is misdiagnosed as cardiovascular disease by the fog layer, his life safety will not be threatened. However, if a person with cardiovascular disease is misdiagnosed as a health condition and misses effective treating, his life safety will be greatly threatened.

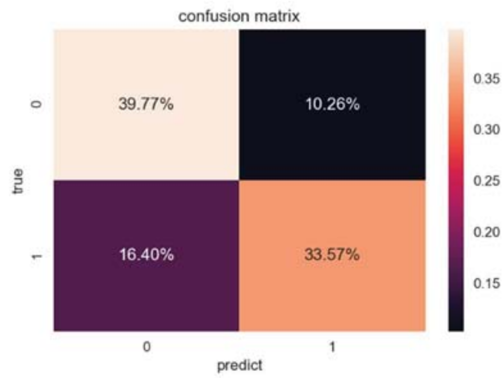


Fig. 7. Confusion matrix for the proposed ANN.

The confusion matrix for the proposed ANN is as shown in Fig. 7. Through observation, we found that FN accounts for 16.40% of the entire test set, and TP accounts for 33.57% of the entire test set. Therefore, the efficiency of the proposed algorithm for anomaly detection can be considered to reach 83.60%. But the accuracy rate of cardiovascular disease patients can be found is only 67.18%.

## V. CONLUSION

In this paper, we proposed a real-time big data healthcare analysis system based on the combination of shallow neural network and deep neural network. The system consisted of two parts: the detection of fog layer abnormality based on shallow neural network and the diagnosis of cloud disease based on deep neural network. The system can not only make full use of the real-time nature of the fog layer, but also make full use of powerful computing power of the cloud layer. We analyzed the fog layer anomaly detection based on the shallow neural network. The diagnosis rate of cardiovascular patients was 67.18%. In the following work, we will make further analysis on how to improve the diagnostic rate of abnormal detection.

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