Received May 28, 2021, accepted June 6, 2021, date of publication June 10, 2021, date of current version June 18, 2021.
Digital Object Identifier 10.1109/ACCESS.2021.3088262

Optimization of IoT-Based Artificial Intelligence Assisted Telemedicine Health Analysis System

HENG YU AND ZHIQING ZHOU
School of Information Engineering, Pingdingshan University, Pingdingshan 467000, China
Corresponding author: Heng Yu (2540@pdsu.edu.cn)

ABSTRACT This paper presents an in-depth study and exploration of the health IoT architecture and related implementation technologies from both theoretical and practical aspects, with important theoretical significance and practical application value. The research includes cloud fusion health IoT architecture, multimodal information acquisition in health IoT perception layer, multi-level service quality assurance of health IoT based on human LAN, and emotional perception and emotional interaction in health IoT. In terms of health IoT architecture, the cloud convergence health IoT architecture is proposed to deeply integrate the health cloud platform and perception layer by integrating multiple communication technologies to optimize the user experience and make health IoT applications more closely connected with people. This paper describes the basic concepts and main components of multimodal sensing information collection, the design and implementation of a health monitoring cloud robotics platform, robotics-based multimodal data sensing and aggregation, and high comfort sustainable physiological signal collection based on smart clothes. The feasibility and performance of the QoS framework proposed in this paper are verified by computer simulations. In this paper, migration learning is used to implement emotion data labeling, continuous conditional random fields to identify emotions based on data collected from smartphones and smart clothes, respectively, and finally decision layer fusion for emotion classification prediction.

INDEX TERMS Internet of things, artificial intelligence, telemedicine, health monitoring, data analysis.

I. INTRODUCTION

After the rapid development and evolution of IoT technology in the last decade, it has gradually transitioned from the early theoretical research and the exploration stage to the practical deployment and application stage, which have produced many representative IoT applications in some application fields [1]. At present, IoT is in the stage of expansion and penetration of early coordination network and Radio Frequency Identification (RFID) applications to various levels of the national economic and social life, and the new application scenarios and demands put forward higher requirements for traditional Internet of Things (IoT) [2]. At the same time, as the Internet of Things is a cross-discipline involving sensors, microelectronics, computers, communications and other technical fields, the Internet of Things will face more technical challenges than ever before. In the ''people-oriented'' health IoT concept, more attention will be paid to the quality of service (QoS) and the quality of experience (QoE) and other important evaluation indicators of the IoT, how to apply some of the latest technology, and How to apply some of the latest technologies and research results to health IoT and improve the service level has become an urgent technical challenge [3], [4].

Telehealth monitoring service integrates health care resources to extend the coverage of health care institutions, which can essentially be understood as a telemedicine health digital system for communities, families, and convalescent and rehabilitation institutions, and the service targets cover almost all people [5]. From injured people in disasters, maternity, newborns, elderly patients, disabled people, chronic disease patients, emergency patients and people in the sub-healthy state, etc., all may become service targets, and its application areas range from the study of human physiological state under extreme conditions, the development of emergency medicine, to the improvement of medical level in remote areas and family healthcare for thousands of families, which will break the existing medical service pattern [6]. It will improve the relationship between doctors and patients, extend the service radius, enlarge the utilization of medical resources, enhance the accessibility of quality resources, reduce the overall cost of medical

The associate editor coordinating the review of this manuscript and approving it for publication was M. Shamim Hossain.

and health services, and provide timely medical and health protection [7].

With the maturity of technology and the demand for applications, IoT is attracting increasing attention in the field of health services. In recent years, with the popularity of mobile communication devices, a huge market space has been created for the healthcare sector [8]. However, few successful applications use IoT technology to bring health services to families, to individuals and to provide personalized health services. Health IoT is an important branch of IoT application, and the change of health service model it brings will not only benefit most users but also promote the development of the health service industry [9], [10]. Currently, there are some representative applications of IoT in the medical industry, health monitoring, sports promotion, and spiritual comfort.

With the rapid integration of IoT technology and traditional medical information system, the clinical medical application based on the wireless network is getting increased attention for its quick and convenient and future development trend [11]. IoT-based medical information technology has developed in the era of mobile medical care. Doctors can carry mobile clinical terminals to complete almost all medical work, which greatly improves the efficiency of doctors and provides better diagnosis and treatment services for patients. The typical architecture of health IoT in the medical industry is shown in Figure 1, where the IoT integrates and optimizes the resources of the whole hospital to improve the efficiency of services [12]. Due to the high degree of specialization and difficulty of implementation, this kind of IoT application in the medical industry can only be adopted within professional medical institutions and is not suitable for the general population [13].

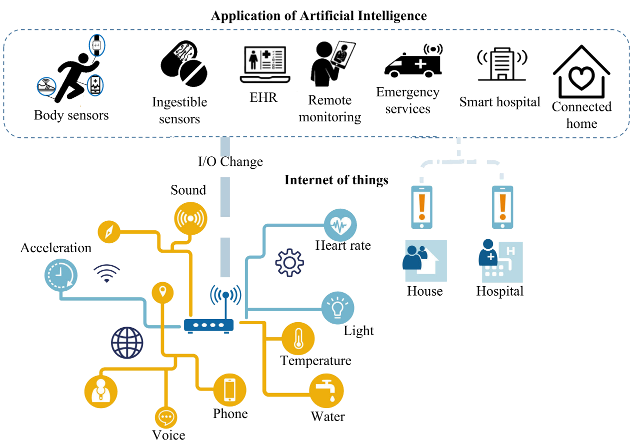

FIGURE 1. Health IoT architecture for the healthcare industry.

The home-based remote health monitoring application integrates physiological signal sensors, wireless communication technology, and cloud computing, overturning the traditional health monitoring model and becoming an important branch of health IoT development [14]. Because the data collected by the sensors can be transmitted to cell phones, which are connected to the sensor nodes via Bluetooth, and send the received data to the backend health management service platform, thus realizing health monitoring anytime and anywhere [15], [16]. This application is particularly suitable for the elderly, chronic disease patients, and sub-healthy people. Through various advanced mobile, portable, and low-power intelligent health sensing devices, the physiological indicators that can be detected include blood oxygen, pulse rate, blood pressure, blood sugar, bone density, Electrocardiograph (ECG), body temperature, respiration, etc. [17], [18].

The service model of health monitoring is divided into two types: family-based monitoring and community-based monitoring. Community-based health monitoring systems connect patients with medical and health experts through physiological signal sensing devices, wireless communication, and a cloud-based health service platform, which allows medical and health experts to understand the user's physiological indicators and provide guidance on the user's disease treatment and health plan [19]. The architecture of a home-based health monitoring system, on the other hand, is relatively simple and usually requires only the purchase of a dedicated health-aware device to use [20]. These devices are usually connected to smartphones using Bluetooth, transferring the detected physiological data to the cell phone, and then viewing the test results and saving historical data in real-time through a special health application installed on the cell phone, and some device manufacturers also provide value-added services such as uploading data to cloud servers, querying historical data, and personalized health guidance [21]. According to the continuous monitoring of physiological indicators, health monitoring is divided into two types of continuous monitoring or intermittent monitoring. Some special physiological indicators need to be monitored continuously to find out whether the indicators are abnormal [22].

This thesis proposes a cloud-converged health IoT architecture, which integrates the health cloud platform with the sensing layer deeply by integrating multiple communication technologies to optimize the user experience and make the health IoT application more closely connected with people [23]–[25]. The whole architecture consists of the health IoT perception layer, transmission layer, and health cloud service layer. The health cloud service layer consists of health cloud service support sub-layer and health cloud service application sub-layer. The hierarchy and components of the architecture are described in detail. A typical architecture of cloud-converged health IoT for specific applications is given. This paper introduces the basic concepts and main components of multimodal sensing information acquisition, design and implementation of a cloud robotics platform for health monitoring, robotics-based multimodal data sensing and aggregation, and high comfort sustainable physiological signal acquisition based on smart clothes. To verify the feasibility of the designed health monitoring system and evaluate the performance indicators of the system, relevant underlying hardware systems, embedded software, and upper layer health application software are developed based on the real

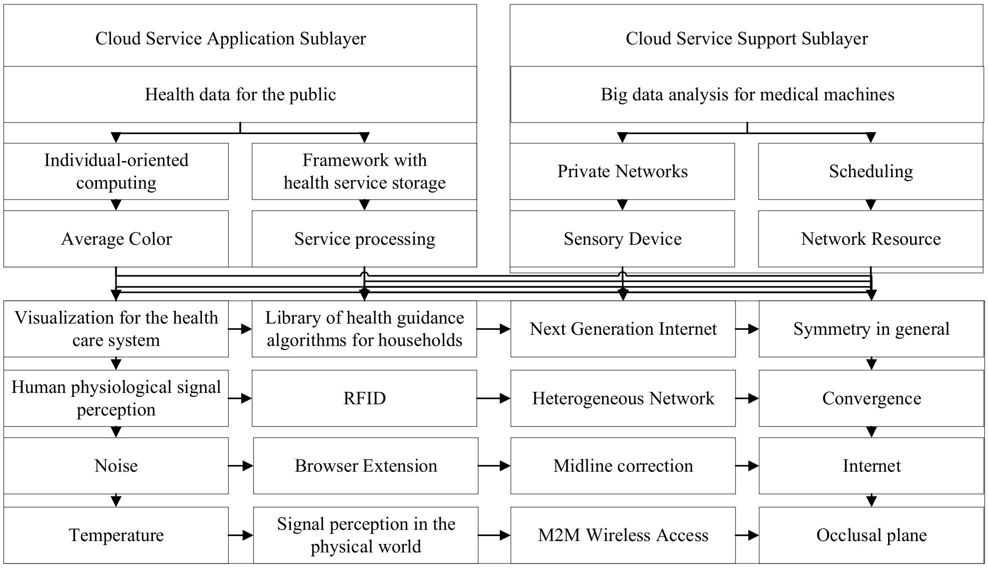

FIGURE 2. Health IoT architecture for cloud convergence.

hardware and software platform [28]. This paper also provides an in-depth analysis of the quality-of-service assurance requirements in health IoT and proposes a quality-of-service assurance framework based on a multi-level priority policy. To verify the feasibility of the proposed framework and evaluate the performance metrics of the framework, a custom simulation model is developed based on a network simulation platform, and the experimental results show that the proposed framework can meet the requirements of the health IoT in terms of diversity and performance of QoS assurance.

II. ARTIFICIAL INTELLIGENCE-BASED CLOUD CONVERGENCE FOR HEALTH IOT ARCHITECTURE

A. ARTIFICIAL INTELLIGENCE-BASED HEALTH IOT ARCHITECTURE DESIGN

The health IoT perception layer has two objectives, to collect various raw signals from the objective world, whose main components are different types of sensor devices, and to collect various physiological signals related to human health [26]. To facilitate the transmission of sensory data, the perception layer usually requires pre-processing of the collected raw signals. Besides, short-range wireless communication is also an important component of the sensing layer for transmitting the collected data to the upper layers [27]. Since people are the most important signal acquisition targets and service recipients in health IoT, the human local area network is particularly important in the perception layer [28]. In many complex signal acquisition scenarios, multiple sensing nodes need to be invoked to work together, and collaborative communication between these sensing nodes also requires the use of short-range wireless communication technologies in the sensing layer. The main challenges facing the sensing layer include sensor technology, node security, embedded operating systems, and multi-protocol gateways. In this paper, we propose a three-layer architecture of health IoT with cloud convergence including health IoT sensing layer, health IoT transmission layer, and health cloud service layer [29]. The health cloud service layer is further divided into cloud service support sub-layer and cloud service application sub-layer, as shown in Figure 2. The functions and components of each layer are briefly described below.

Wearable devices have become a very important way to obtain physiological data at the sensory level in the health IoT. Wearable devices mainly collect various physiological parameters from the human body, including the EEG, ECG, blood pressure, blood oxygen, respiration, electromyography, and other signals. These devices are mainly in close contact with the human body and can be worn or implanted in the human epidermis, which can collect, condition, amplify and quantify the physiological signals of the human body, and transmit the quantified data to the external network communication access equipment in a wireless way. Since the human body may wear multiple wearable devices at the same time, the possible mutual interference between these devices and the priority of data transmission has become important technical issues to be solved in the health IoT sensing layer. The following is a brief description of the traditional wearable device signal acquisition devices and the physiological signal acquisition based on smart clothes proposed in the paper.

In this paper, we propose introducing wearable smart clothes to collect human physiological signals in the health IoT sensing layer. A variety of miniature physiological signal acquisition sensors are integrated into the smart set to realize the acquisition of multimodal physiological signals. Bioelectrical signals in the human body are important indicators of human vital signs, and disease diagnosis and health condition assessment usually require obtaining various bioelectrical signals from the human body in the Chapter 2. Electrodes are one of the most important technologies for bioelectric signal acquisition, and in recent years, textile structured electrodes have made remarkable progress in the fabrication process and lifetime, and the use of textile structured electrodes to measure and monitor human bioelectric signals has received widespread attention in Chapter 3. Therefore, the paper proposes the use of textile dry electrodes as the sensing component of electrical signals and the integration of textile dry electrodes and clothing in one, which overcomes the user's psychological feeling of being monitored while improving the user's comfort and realizes the monitoring of bioelectrical signals anytime and anywhere in Chapter 4. Compared with traditional disposable electrodes, textile structure electrodes have the advantages of being soft, breathable, moisture permeable, washable, and can be used in a dry state without causing skin irritation for a long time, which is especially suitable for a long-time use [30]. Wisdom clothing can collect a variety of human physiological signals. The following is only the human ECG signal, respiratory signal and heart rate, and oxygen saturation as an example to introduce the physiological signal collection technology based on wisdom clothing. Since the wisdom garment uses washable textile dry electrodes, users can monitor ECG signals, respiratory signals, heart rate, and other physiological signals by putting on the wisdom garment, and the collected signals can be used for disease diagnosis, health condition assessment, and other applications in Chapter 5.

B. HEALTH IOT TRANSPORT LAYER AND AI-CLOUD SERVICE LAYER DESIGN

Semantic understanding and knowledge representation of multimodal data allows intelligent bodies to perceive and understand real data scenarios in greater depth and can further reason about the perceived knowledge to better support industry applications, such as intelligent Q&A, dialogue systems, human-computer interaction, and recommendations, etc. The health IoT transport layer plays a role of carrying the upper and lower layers, sending control commands from upper-layer applications to sensing nodes through IoT gateways and receiving data collected from the sensing layer, and using various network technologies (including mobile communication networks, Internet, and other private networks) to transmit data to upper-layer applications and realize the interface with upper-layer applications [31]–[34]. The main challenges facing the transport layer include the convergence of existing networks with the perception layer networks. Existing networks and perception layer networks are very different in terms of protocol design and communication mechanisms, and it is an important challenge to achieve the interconnection and interoperability of networks. The current solution is to use multi-protocol gateways, but the complexity of network technologies and specifications and the speed of updates are increasing, making it more difficult to develop IoT gateways. Therefore, it is still difficult to find a universal solution [35]. The scope of health IoT is wide, ranging from large health IoT covering a wide area to small health IoT covering one unit, so the network technologies and communication needs involved are very different, so the multi-network convergence technology based on the actual needs of health IoT is a major technical challenge for its development. Existing network technologies are designed to be constrained by the technical background and application requirements of the era they are in, and there are serious deficiencies in scalability, etc [36], [37]. Moreover, these networks have been in operation for many years, with huge investment in equipment, and manufacturers usually do not disclose technical details to make high profits, which seriously restricts technological innovation and cannot adapt to the urgent need for network technology change for emerging applications such as IoT. Therefore, it is an arduous task to carry out innovative research on network technologies for emerging applications such as the Internet of things for health under the premise of guaranteeing the normal operation of existing networks and the initial investment.

The main task of the cloud service support sub-layer is to compress, store, format convert, and analyze the collected physical world data and human physiological data, which are important support for the upper layer of health IoT services and application systems. Since the amount of data generated by terminal devices connected to IoT grows, this layer requires a massively parallel computing cluster based on cloud computing technology to process the sensed massive data in real-time and realize advanced analytical functions such as intelligent information processing, data mining, and analysis and prediction on this basis. The computing and storage resources in the analysis layer in large IoT architecture are usually resource pools based on virtualization technology, and the system dynamically allocates and recovers resources according to the demand of analysis tasks to achieve optimal resource utilization. In addition to traditional data analysis methods, the analytics layer also needs to select other analysis methods based on specific data types and application requirements. The IoT generates a large amount of unstructured data, and the processing capability, processing efficiency, and related algorithms for this kind of data also face great challenges.

In recent years, numerous research results in the field of sensors have driven the popularity of home health monitoring systems and the development of various health monitoring devices capable of accurately measuring and analyzing human physiological data. Nevertheless, there is still a conflict between the comfort and wearability of the device and the type of physiological data collected, and the battery life. As shown in Figure 3, while providing users with high QoS and QoE health monitoring services, this paper gives a typical architecture for building a cloud-fused health monitoring system based on a mobile robot collecting environmental information and human physiological data and integrating cloud computing technology. The data in health monitoring systems are characterized by large data volume, various data types, high dimensionality, and rapid changes. Traditional data storage and processing technology can no longer meet

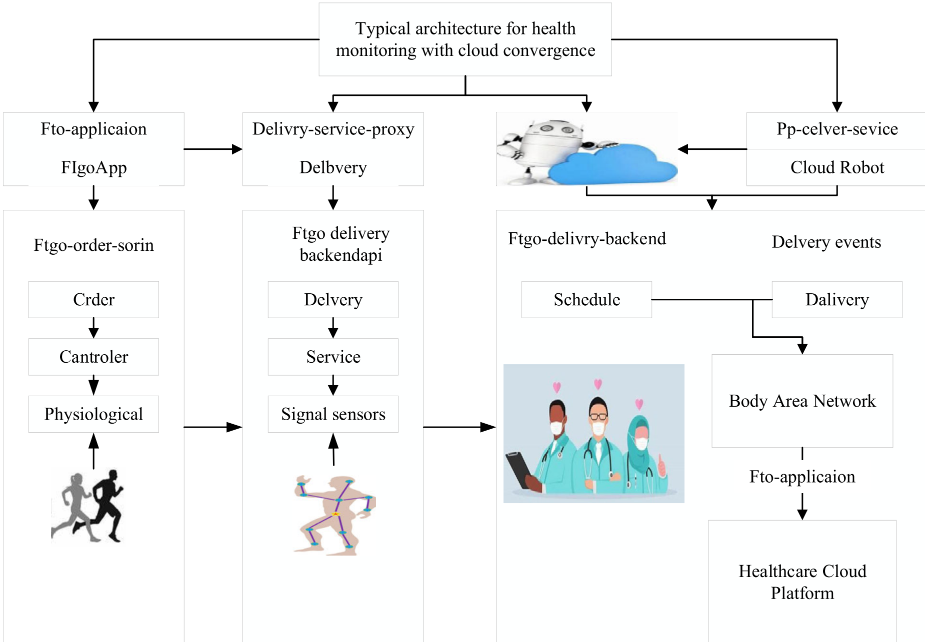

FIGURE 3. Typical architecture of health monitoring with cloud convergence.

the demand for fast access and efficient processing of data in health monitoring systems. The rapidly emerging cloud computing and big data technology can solve the data storage and processing problems faced by the health monitoring system.

The integration of wearable computing, robotics, and cloud computing technologies with health monitoring systems will greatly improve the quality and service level of health monitoring services. The health monitoring system proposed in this chapter consists of four parts: the end-user, wearable smart clothes, robot, and health cloud platform. The human physiological data are collected through wearable health devices, and then the robot or smartphone forwards the collected health data to the remote health cloud platform. The robot's role in the overall system includes sensing environmental information, saving and transmitting sensing data, performing human-machine interaction, and integrating wireless communication modules. The cloud is responsible for storing large-scale health data, building health models, providing personalized health services based on analysis and prediction of health big data, and other functions.

C. DETAILED DESIGN OF IOT-BASED AND AI-BASED TELEMEDICINE HEALTH ANALYSIS SYSTEM

The telemedicine system provides the management function of the IoT gateway, including the registration, login, and release of the IoT gateway. The telemedicine system receives medical monitoring data encapsulated in UMMP protocol from the IoT gateways over the network, which at this stage includes fat, blood glucose, blood pressure, oxygen saturation, and ECG data, decodes and analyzes these data and stores the monitoring data and the time of collection in the database. General users and health professionals can log in to the telemedicine system from their personal computers via a wired or wireless network connection via a browser to view and monitor all medical data of general users in real-time.

The telemedicine system is divided into three subsystems, including the basic platform subsystem, the application platform subsystem, and the specific application subsystem. The basic platform subsystem manages the IoT gateway according to the UMMP protocol and receives medical monitoring data from the IoT gateway. The basic platform subsystem also manages the database and stores the basic information of users and medical monitoring data. The base platform subsystem receives subscription requests from the application platform subsystem and the specific application subsystem and provides medical data.

The application platform subsystem provides a user login function and offers different display interfaces and functions according to the user's attributes. The application platform subsystem receives user medical data encapsulated in ECG protocol from the base platform subsystem and then displays them on the user interface as historical trend graphs and ECG waveforms after preliminary analysis as needed. The application platform subsystem requests real-time monitoring functions from the base platform subsystem and updates the user interface based on the received data.

Wavelet transform uses finite-length or fast-decaying oscillating waveforms to represent signals. The mother wavelet is the last function whose integral is zero, as shown in (1). The wavelet is generated by a single wavelet basis function called the mother wavelet, which is generated by expansion and contraction, as shown in equation (2).

Among them, ψ is the scale parameter, u is the translation parameter, and the continuous wavelet transform (CWT) is shown in equation (3).

$$\oiiint_{D} \frac{\psi(t)-1}{\psi(t)+1} dt = 0 \tag{1}$$

$$\psi(t) = \frac{\psi(t-u) \times \psi(s)}{(t-s)s} \tag{2}$$

$$W = \frac{\sqrt{a}}{2\pi} \int f(t-u) f(s) dt \tag{3}$$

This article chooses discrete wavelet transform to process the ECG signal. Discrete wavelet transform discretizes both the scale parameter s and the translation parameter u, often taking s>0 and u>0. The discrete wavelet function is defined here as formula (4):

$$W = a_0 \psi(\frac{at-k}{at+k} + b_0) \tag{4}$$

Here we use the obtained wavelet transform coefficients to reconstruct the signal and further define the discrete wavelet change as equation (5):

$$C = \frac{\sum f(t)}{\int \psi(t) dt} \tag{5}$$

The specific application subsystem includes the medical analysis module. The medical analysis module can receive user medical data encapsulated in ECG protocol from the base platform subsystem, unpack the data according to specific requirements, and then analyze and process it through the model of hypoxia or heart rate disorders, display the relevant information of the user and provide real-time alarm functions according to the analysis and processing results. The application-specific subsystem also includes an online consultation module.

The system is designed for medical data monitoring, mainly to monitor the medical data of users. First, if the logged-in user is a patient, then select the type of medical data to be queried, if the logged-in user is a health professional, first select a patient-user and then select the type of medical data to be queried, then the system listens to the medical data in the listening thread, receives and decodes the received medical data, prompts the user to receive the latest medical monitoring data, and updates it to the trend graph or ECG waveform graph.

After users log in to the telemedicine system, general users can query their historical medical data, and health experts query the historical medical data of the general users they provide services to. Both health experts and general users can view the latest collected fat, blood oxygen, blood pressure, and blood glucose data within a specified amount. Both health professionals and general users can view trend graphs of historical facts, oxygen, blood pressure, and blood glucose data over a specified period. The ECG data historical review can be displayed in pages, with each page displaying 10 seconds of ECG waveform and the ability to automatically refresh the timeline time markers when the page is turned. After the user logs into the personal monitoring platform, the general user can monitor his real-time medical data, and the health expert can monitor the real-time medical data of the general user whose services he provides. For each medical data received from the IoT gateway, if the general user corresponding to the gateway is being monitored by himself or his corresponding health expert in real-time, the telemedicine system can display the latest medical data to the user while storing the medical data.

III. ARTIFICIAL INTELLIGENCE ASSISTED TELEMEDICINE HEALTH ANALYSIS SYSTEM ANALYSIS SYSTEM PERCEPTION INFORMATION ACQUISITION

A. HEALTH IOT PERCEPTION LAYER MULTIMODAL INFORMATION ACQUISITION

Cloud computing is a new computing and service model that provide resource services to users based on the Internet, through which pooled software, hardware, and network resources and information can be provided to service requesters according to actual need. In the cloud computing environment, users no longer need to build their infrastructure, nor do they need to understand the details and expertise of the infrastructure in the ''cloud''. In this paper, we design a mobile robotics architecture based on 5G-ATE technology and integrating the latest technologies such as cloud computing and big data, and implement a real robotics system based on the proposed architecture. Since the proposed architecture is highly scalable, it is suitable for various application scenarios of robotics. A robot system with emotion recognition and feedback is implemented on top of the proposed robot architecture, which can better enhance the robot intelligence and improve the user experience. The rest of this section is organized as follows: Research progress of wireless communication robot, LTE-based mobile cloud robot architecture, design and implementation of the robot control part, and implementation of robot application software.

The progress made in the field of mobile communication technology and artificial intelligence, networking, mobility, and intelligence has become the development trend of robotics. In this paper, based on the integration of 5G-LTE mobile communication technology, cloud computing, big data, and machine learning, an intelligent mobile cloud robot architecture is proposed, as shown in Figure 4. The robot system architecture includes four components, including a humanoid robot, a 5G-LTE network, the intelligent control terminal of a robot supporting LTE communication, and a cloud platform. Among them, the robot is the front-end for interaction with the user, including the physical structure of the robot, the ARM microprocessor for controlling the robot, various sensors, the 5GLTE communication module, and the Android development platform that provides more advanced robot functions.

The Android development platform transmits data with the ARM development board via Bluetooth, and the communication between them adopts self-developed communication.

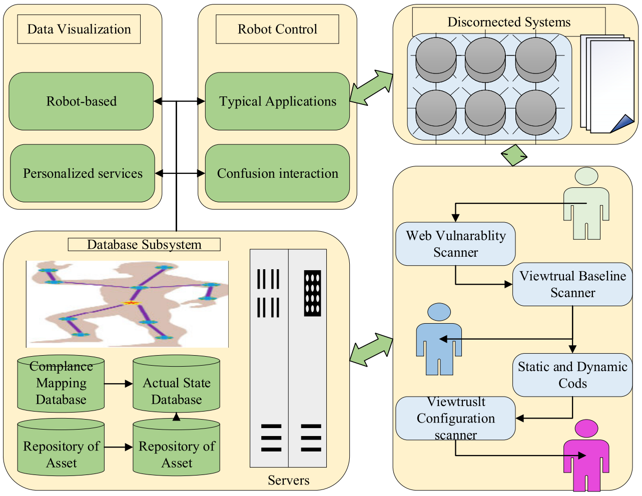

FIGURE 4. LTE-based mobile cloud robot architecture.

The communication between them uses self-developed communication standards to enable high-level application software to send hardware control commands to the robot and to receive sensing data collected by sensors on the robot. The robot is connected to the remote robot control terminal and the cloud platform through the LTE communication module. Due to the use of LTE communication technology, communication bandwidth is guaranteed, and users can turn on the robot body camera through their LTE terminals to observe the robot's surrounding conditions in a real-time video format. It is also possible to view the sensing data collected by the robot and send control commands to the remote robot through an application installed on the user's terminal.

This robotics architecture integrates the data analysis and learning capabilities of the cloud platform to enhance the human-robot interaction capabilities of the robot and to give the whole robotics system more "intelligence". The architecture is suitable for a variety of robotic applications, such as developing robotic applications that can recognize human emotions. The cloud platform records the environmental signals collected by the robot's sensors, audio, and video information, integrates the user's social network dynamics and the user's active feedback, and intelligently issues feedback commands to the robot based on the emotion recognition and feedback algorithm.

In the tree structure, when the priority of the node under the router is changed, the priority of the router needs to be changed accordingly. The priority of the router is the weighted average of the priority of each child node, and the calculation method is shown in equation (6):

$$P = \int S_i dt \times \int P_i dt \tag{6}$$

The maximum address allowed in the network is calculated by equation (7):

$$A = \frac{Rm + n}{C \times skip(d)} \tag{7}$$

The time slot matching identification process can be seen as multiple Bernoulli tests, which translates into a binomial distribution of mathematical problems. The specific probability is expressed as:

$$R(X = k) = C_m^k \cdot \left(\frac{5}{T}\right)^k \cdot \left(10 - \frac{5}{T}\right)^{m-k+1} \tag{8}$$

In Eq. (8), K and T denote the corresponding parameters according to the values, and the values of the curves are obtained by processing according to this formula. The probability of a successful time slot, i.e., a time slot with only one label choice, is derived from the above equation.

$$R_g = R(X = 1) = C_m^1 \cdot \left(\frac{5}{T}\right) \cdot \left(10 - \frac{5}{T}\right)^{m-1} \tag{9}$$

Similarly, the probability of an idle time slot, i.e., a time slot without any label selection, when k is zero is given by:

$$R_e = R(X \geq 2) = \sum_{i=1}^{m} C_m^i \cdot \left(\frac{5}{T}\right)^{i+10} \cdot \left(10 - \frac{5}{T}\right)^{m-i-9} \tag{10}$$

B. TELEMEDICINE HEALTH ANALYSIS SYSTEM PERCEPTION APPLICATION IMPLEMENTATION

Robot-related application software is developed based on the Android platform. The local application runs on the LTE phone on the robot, and the user's LTE smart mobile terminal runs the robot's remote management software, which establishes network communication with the robot through the telecom operator's LTE network. The cloud platform then runs applications related to the robot's intelligence. This section describes the design and implementation of the robot's remote control software, which mainly includes the following functional modules: UI module, robot control module, the voice recognition module, sensor data processing, and display module, and remote video transmission module.

The UI module completes the interaction and remote communication with the user and calls other functional modules according to the user's operation. the open button is used to establish the network connection with the cloud platform or the robot. hold and speak button is responsible for turning on the voice recognition function to control the robot by voice. The video button is used to turn on the camera to realize the remote real-time video transmission. The base button is used to switch the robot parts controlled by the program, when it is base, it is responsible for controlling the robot's walking, when it is head, it is responsible for controlling the robot's head movement. Send button is responsible for manually sending the robot's current status to the cloud platform.

The robot control module realizes remote control of the robot through the user's LTE mobile smart terminal, and at the same time, the user can also log into the cloud platform to realize control of the robot. The specific process of controlling the robot through the cloud platform is as follows: the LTE mobile smart terminal establishes a network connection with the cloud platform, the cloud platform establishes a network connection with the target robot, the user transmits control commands to the cloud through the control software, the commands are transmitted to the LTE Mobile Phane on the robot through the cloud platform, and the LTE Mobile Phone on the robot The commands are transmitted to the LTE Mobile Phane on the robot through the cloud platform, and the LTE Mobile Phone on the robot transmits the commands to the robot's main control board via Bluetooth.

The voice recognition module implements user-robot voice interaction and control of the robot, integrating local offline voice recognition and cloud voice recognition. Basic control commands for the robot are implemented locally as offline speech recognition. Complex natural language recognition tasks are offloaded to the cloud for implementation. After receiving the speech recognition results from the cloud feedback, the speech recognition module performs the necessary analysis and processing, and compares them with the local speech command set and the interactive operation command set to find the optimal result and finally realize the voice interaction with the user. The robot can continuously collect environmental data and transmit it to the robot control program via Bluetooth. The robot control program can display the sensed data locally or transmit the collected data to the cloud platform via LTE network and store it, and the remote user can obtain and display the data stored in the cloud platform or real-time data through the data display module in the application, and can also query the saved historical data.

Real-time video transmission has many important application scenarios in the field of robotics. In the LTE network environment, a certain amount of overhead is often spent to ensure the continuity of the video stream. For the user experience, the real-time video is more demanding than continuity, and it is often not necessary to ensure that every video frame is sent and received. To meet the demand of efficient transmission, the connectionless UDP transmission protocol is used, and a control module and a picture compression module are added based on the UDP protocol to ensure the real-time requirements of the control video transmission, the picture compression module compresses the pictures to different degrees, and the control module monitors the information of the cache queue in real-time and sends control messages to realize the cooperation of data transmission and reception, which realizes the based on synchronous and asynchronous transmission methods. This paper proposes an LTE-based mobile robot architecture using humanoid robots, details the components of the robot architecture, and designs and implements a robot system based on the proposed architecture, and finally implements an emotional interaction robot based on the proposed architecture to verify the feasibility and scalability of the proposed robot architecture.

C. ARTIFICIAL INTELLIGENCE-BASED MULTIMODAL SENSING DATA AGGREGATION

The main acquisition components on the robot side include the microcontroller and the main controller. The microcontroller is the front-end of data acquisition, which controls the wireless communication module worn on the user's body to collect the user's physiological data and sense the environmental information around the user through the environmental sensors built on the robot. The microcontroller transmits the received data to the robot's main controller. Finally, the expert controller sends the data in AML data format to a remote cloud platform for storage and analysis.

Sensors built into the robot for sensing environmental information include temperature sensors, humidity sensors, harmful gas sensors, fiber optic sensors, etc. Human body sensors worn on the user's body include body temperature sensors, blood pressure sensors, heart rate sensors, blood oxygen sensors, blood glucose sensors, electromyographic sensors, etc. Since sensor devices with built-in microprocessors and peripherals can perform the task of collecting data independently, they are relatively easy to integrate into the system. To facilitate the collection of multiple sensing data, the design is dedicated to the specific identification of each sensor, so that various sensing data can be aggregated using appropriate methods based on the sensor categories. To reduce the overall power consumption of the system, an 8-bit microprocessor and a simplified miniature embedded operating system are used to control the work of the microcontroller. A common set of application program interfaces is designed and implemented based on the embedded control system, and all the operations of the underlying hardware are done through this public API. When new hardware needs to be added or extended, only drivers for the new hardware need to be written, and no application changes are required. The main robot controller uses a 32-bit high-performance ARM processor with 1 TB running memory and an Android operating system, and its tasks include transmitting sensing data using a wireless network, providing a user interface, and interacting with the user.

The Android half-tablet is used by mobile device manufacturers for release and good concurrent answerability. The system is based on the android platform to develop the upper layer health monitoring software system. The whole software system is divided into two parts, client, and server, involving the development of the underlying embedded hardware and android platform application software development. Through the development of the underlying hardware interface layer to achieve Android platform control of the underlying hardware; through the integration of Wi-Fi and 5G communication methods to achieve remote control of the robot, real-time video transmission, and other functions; through the connection with the Android, development board to monitor and present a variety of human health and indoor environment-related sensing data. The software system also has an emergency response mechanism, which can notify family members by phone, SMS, and real-time remote video in case of an emergency. The software system also integrates intelligent voice recognition and speech synthesis technologies to facilitate the use of the robot by users. To verify the feasibility of the designed health monitoring system and evaluate the performance indicators of the system, this paper develops the underlying embedded system and the upper health application software involved in the system based on the real hardware platform.

The test system realizes the sensing and aggregation of environmental information such as temperature, humidity, and harmful gases, and the human physiological signals that can be collected include heart rate and blood pressure. The data collection and aggregation operations are shown in Figure 5.

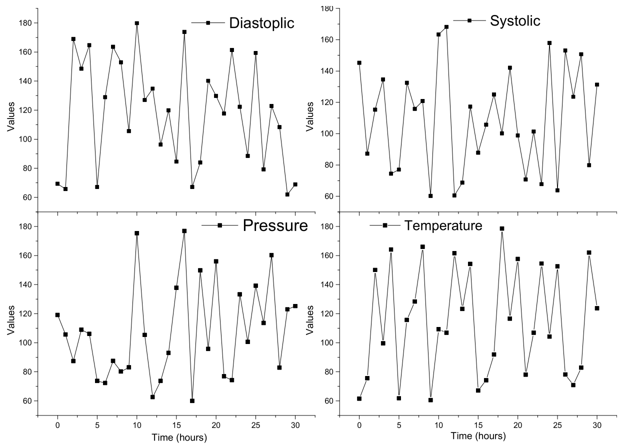

FIGURE 5. Multimodal sensing data aggregation.

D. IoT-BASED REMOTE HUMAN INFORMATION COLLECTION, ANALYSIS, AND PROCESSING

ECG reflects the electrical activity of the human heart and is one of the most commonly used indicators in clinical medicine. It can help diagnose arrhythmias, myocardial ischemia, myocardial infarction, and determine the effect of drugs or electrolyte conditions on the heart, and is an important basis for doctors to diagnose clinical diseases. Besides, ECG is also an important way to detect people's emotions as they fluctuate and cause corresponding changes in the ECG. ECG measurement is highly specialized and requires the placement of multiple electrodes on the human body, which makes it less portable and more difficult to operate.

Since the human body's ECG signal strength is low and is highly susceptible to interference from the surrounding environment as well as the human body itself (e.g., the movement of human limbs), the original ECG signal collected through the smart clothes has interference noise, which will have a greater impact on subsequent medical applications and sentiment analysis. Besides, because the collected ECG signals are like continuous time-domain signals, information about the features of the user's ECG is not available from the raw ECG data, which is necessary for the sentiment analysis algorithm. Therefore, acquired raw ECG signals must first be pre-processed to eliminate the interfering signals. Then, the ECG signal is analyzed to extract ECG features that can be used for later sentiment analysis.

The detection of the QRS wave group is the basis of ECG band signal detection, while the detection of the wave crest

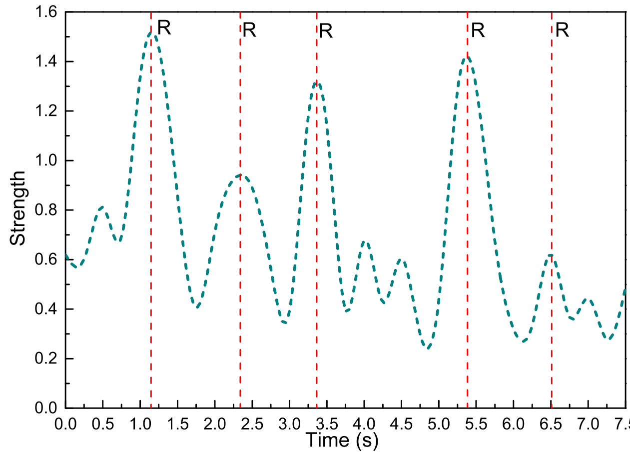

FIGURE 6. Typical adult ECG data analysis.

is the basis of the QRS wave group detection side. First, the ECG signal after pre-processing to find the first-order difference, and then set a first-order difference threshold, if the first-order difference is greater than the Min value, the point may be in the rising part of the R-wave, according to this feature can find the R-wave peak. As shown in Figure 6, the R-wave peak found in this way may be misdirected, and the misdirected wave peak needs to be removed. Since the R wave cannot appear twice in 0.25 seconds, it is necessary to filter the two peaks that appear within 0.5 seconds and compare the amplitudes of the two peaks, with the larger amplitude being the actual wave and the smaller amplitude being the misdirected wave.

IV. TELEMEDICINE IOT EMOTIONAL PERCEPTION AND EMOTIONAL INTERACTION

A. TELEMEDICINE EMOTIONAL INTERACTION APPLICATION FRAMEWORK DESIGN

The main innovation is the combination of this section for the first time. This section proposes that the framework of cloud-converged health IoT emotional interaction application consists of four layers: the emotional information acquisition, emotional interaction control center, emotional interaction carrier, and end-user. The emotional information acquisition layer collects emotion-related data from the perception layer of the health IoT and then transmits these data to the emotional interaction control center. The emotional interaction control center identifies the user's emotional state by using the emotional knowledge base and emotional data constructed in advance; the emotional interaction agent receives the emotional recognition result and realizes the emotional interaction with the end-user by controlling the emotional interaction carrier.

Emotion-related data acquisition is the basis for emotional perception and emotional interaction, and the rise of smart mobile devices and wearable devices has facilitated the acquisition of emotional data. The smart clothes designed and implemented in this paper have great advantages in acquiring emotion-related physiological data. Emotional interaction carriers have an important role in the overall application framework, and as robots become increasingly functional, making they the best emotional interaction carriers. Take the health monitoring robot as an example, it has conventional health monitoring functions, but when the robot is integrated with the emotional interaction component of the health cloud it can conduct emotion-based human-robot interaction with the user. The emotional interaction methods supported by the service robot include music, video, movement, dance, LED lighting, voice synthesis, etc. The robot can also be used with smartphones and smart homes. The robot can also be used in conjunction with smartphones and smart home devices to interact with users emotionally.

The cloud analyzes the user ECG data uploaded in the application scenario in real-time through the pre-established user ECG data model, and feeds the detected user emotional condition to the user-side emotional interactive medium on time, thus realizing emotional interaction. To improve the accuracy of emotion detection, it is necessary to integrate other data related to user emotion in the cloud to assist the detection of emotion. Using a big data processing platform, various machines learning algorithm libraries, and developing emotion detection algorithms based on ECG data, we finally realize the emotion detection system based on big data and cloud computing.

The ECG signal of the human body is closely related to emotion and can be used to detect the emotional state of a person. First, features related to human emotion are extracted from the ECG signal based on time series, then, the extracted features are used to train the emotion model, and emotion recognition is performed based on the obtained emotion model. In the early stage of system operation, the amount of data is small, which may lead to large emotion detection errors, and users can be involved in correcting inaccurate emotion states, and the machine learning algorithm in the cloud corrects the emotion detection model established based on the results of user feedback. Over time, the accuracy of the sentiment detection system will continue to improve, and eventually achieve personalized user-based sentiment recognition.

B. REMOTE EMOTION DETECTION ASSESSMENT ANALYSIS

The ECG sample data of each volunteer was divided into the training set and test set, and the features were extracted separately, and then the training set was trained and the classification model was generated using a support vector machine, and the test set was applied to the classification model generated after training for classification side trials. Sentiment prediction accuracy of 14 groups of users is shown in Figure 7, and only User 2 and User 7 had lower accuracy, while the sentiment of other users' prediction accuracy of the other users reached an average of more than 60%. Due to the differences in the number of samples of several emotion states in the collected sample data, and the large differences

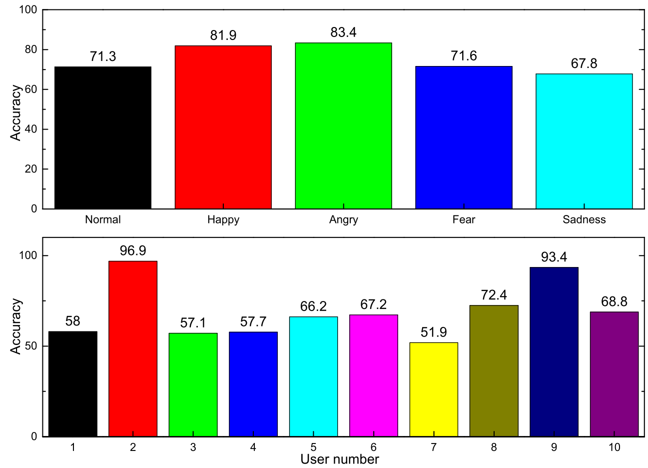

FIGURE 7. Accuracy of user-based sentiment detection.

in the degree of feature expression of each emotion reflected in the ECG signal, the accuracy of the output model during training is affected, which in turn leads to large differences in the accuracy of emotion recognition. The accuracy of angry was 65.74%, and the accuracy of Fear and Sadness was 53.62% and 49.37%, respectively. However, from the above side test results, the overall accuracy is not high and fluctuates greatly, and sometimes the accuracy can be as high as }0Io or higher during the experiment in specific scenarios and specific people. Therefore, it is necessary to consider increasing the latitude of sentiment detection data and adopting new methods to further improve the accuracy and stability of sentiment detection in the subsequent research.

C. TELEMEDICINE IOT HUMAN EMOTIONAL INTERACTION ANALYSIS

As the pace of life accelerates and the pressure of life increases, the number of exchanges between relatives and friends is decreasing and the time spent together is shortening, so much so that personal loneliness is increasing, and increased people are using pets and toys as soul mates. The earlier part of this chapter introduced emotion detection based on ECG signals of wisdom clothes, and emotional interaction applications must be applied with the help of an easily accepted interaction carrier, among the many carriers that can be used for human emotional interaction, robots are undoubtedly the most suitable for emotional interaction with people. Therefore, this paper proposes a multi-functional interactive pillow robot solution that has both practical functions and can soothe the soul and relieve loneliness. The rest of this section includes Pillow robot composition, emotional interaction scenario based on pillow robot, emotional data collection, and processing method, emotional recognition method based on continuous conditional random domain and decision layer fusion method, and emotional interaction demonstration system. Telemedicine uses the computer, communication, and medical technologies and equipment to enable off-site "face-to-face" consultations between specialists and patients, and between specialists and medical staff through the transmission of data, text, voice, and image data over long distances. Telemedicine is not only a medical or clinical issue, but also includes communication networks, databases, and other aspects that need to be integrated into the network system.

To test the accuracy and application effect of emotion detection, 10 volunteers were recruited in the lab for a 10-day test. A background service program and a special APP were installed in the volunteers' cell phones for collecting cell phone data, and the collected data were automatically sent to the emotion detection cloud platform built on the wave Big Data All-in-One. The volunteers collected ECG data by wearing the lab's customized wisdom clothes, and the ECG data collected by the wisdom clothes were sent to the cell phone end via Bluetooth, and then sent to the back-end cloud platform by the special program on the cell phone end, in which the volunteers wore the wisdom clothes for no less than four hours per day. At the same time, a small sensor network was deployed in the lab to obtain information about the volunteers' surroundings, which were also transmitted to the back-end cloud platform in real-time.

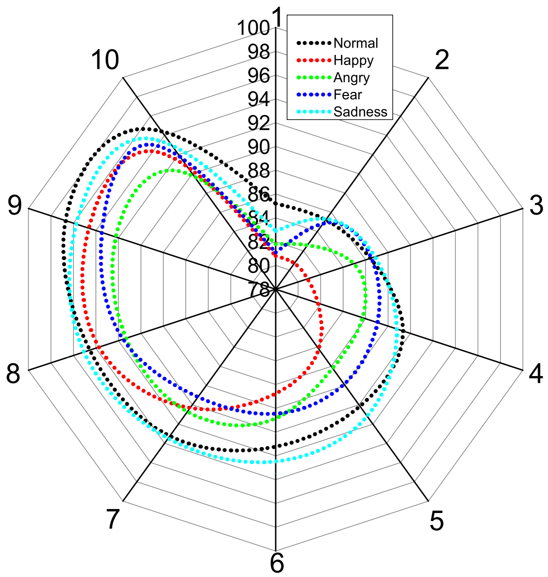

FIGURE 8. The trend of the accuracy of emotion detection.

As shown in Figure 8, it can be found that the sentiment detection accuracy based on multi-source data proposed in this section has significantly improved than the sentiment detection accuracy based on single data of ECM. On the other hand, the back-end cloud platform automatically adjusts the system emotion model according to the emotional state labeling information fed by volunteers, and the system can gradually improve the emotion detection accuracy as the testing time of volunteers accumulates. The accuracy of all five emotional states is relatively low at the beginning of the test, but over time, the cloud-based emotion detection model gradually improves the model by learning the emotion state annotations from the volunteers' feedback, so the emotion detection accuracy gradually increases. However, it can also be found that when the accuracy rate improves to a certain height, the subsequent improvement is very small and basically in a stable state.

V. ARTIFICIAL INTELLIGENCE ASSISTED TELEMEDICINE HEALTH ANALYSIS SYSTEM ANALYSIS SYSTEM SERVICE DECISION OPTIMIZATION

A. ARTIFICIAL INTELLIGENCE ASSISTED TELEMEDICINE HEALTH ANALYSIS SYSTEM ANALYTICS SYSTEM FOR REFERRAL COST OPTIMIZATION

The total system cost is influenced by a variety of factors, and this paper analyzes four key sets of influencing factors: patient unit transportation cost, telemedicine misdiagnosis rate, offline and online unit waiting time cost, and unit service capacity cost. The patient arrival rate of public hospitals can be referred to Xiangya Hospital's, Peking Union Medical College Hospital, and Tongji Hospital, and the arrival rate is calculated to be an average of 14.5 visits per minute in a single public hospital, thus assuming a total arrival rate in the healthcare system. The service capacity cost is mainly reflected in the salaries of remote doctors and offline specialists, and the salary of offline specialist doctors is set to be twice the salary of remote general practitioners. To compare different service strategies in public hospitals, the same values of these parameters are taken under the Gatekeeper service strategy and the dual-channel service strategy.

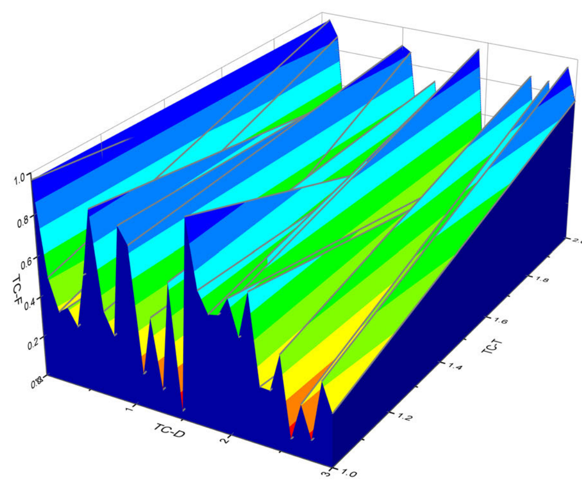

FIGURE 9. Effect of referral thresholds on total system cost.

The geographic distribution of medical resources in China is uneven, with great variability in the level of medical services and medical facilities between urban and rural areas, and relatively high transportation costs for patients in remote areas to access medical care. Figure 9 reflects the impact of unit transportation cost on the total cost of the healthcare system under the three service strategies of public hospitals. When the transportation cost is relatively low, the total cost of the offline service strategy is lower, and as the transportation cost increases, the total cost of the dual-channel service strategy becomes lower. However, when transportation costs continue to increase to a certain value, the total cost of the gatekeeper service strategy is the same as that of the dual-channel service strategy, and both are better than the offline service strategy. When the unit transportation cost is low or the demand for medical services is very small, public hospitals should provide only offline single-channel services, and when the transportation cost is high or the demand for medical services is large, public hospitals should provide offline online dual-channel services, and the change in transportation cost does not make the gatekeeper service strategy the optimal strategy.

Public hospitals use offline service strategies, and the misdiagnosis rate of telemedicine does not affect this healthcare delivery system. As shown in Figure 9, the total system cost increases with the misdiagnosis rate under the Gatekeeper service strategy and dual-channel service strategy, but the total system cost does not increase linearly with the misdiagnosis rate under the dual-channel service strategy. At low levels of malpractice rates, the growth of total costs for the dual-channel service strategy gradually slows down as public hospitals reduce their investment in telemedicine services and more patients make their first visit through offline service channels. When the malpractice rate is above a certain threshold, the total cost of the dual-channel service strategy increases rapidly, in which case hospitals are better off abandoning the telemedicine service channel.

Big data refers to complex data sets that are difficult to be effectively and economically stored, managed, and processed by traditional data management systems. Big data is generally measured in PB and contains structured, semi-structured, and unstructured data. Big data brings severe challenges to data collection, transportation, encryption, storage, analysis, and visualization. The use of big data by medical and health institutions can effectively help doctors make more accurate clinical diagnosis, and more accurately predict the cost and efficacy of treatment plans: integrate patient genetic information for personalized treatment; analyze population health data to predict disease outbreaks.

Telemedicine can play an important role in the management of chronic diseases and has a higher cure rate for some simple diseases. With the rapid development of Internet technology and the gradual improvement of the telemedicine service process, the misdiagnosis rate of telemedicine service will be further reduced, and more diseases can be cured through telemedicine. In the early stage of telemedicine implementation and application, the dual-channel service strategy has stronger superiority and the total cost of the medical service system is relatively low. However, after the telemedicine service has developed to a certain level, the gatekeeper service strategy will be a preferable choice. Therefore, government and medical institutions need to adopt the corresponding telemedicine service strategy by considering the actual situation of telemedicine service applications.

B. ARTIFICIAL INTELLIGENCE ASSISTED TELEMEDICINE HEALTH ANALYSIS SYSTEM AWAITS COST OPTIMIZATION

In this paper, we analyze how the cost of waiting time for patients' offline and online units affects the total cost of the healthcare system. As shown in Figure 10, the total system cost increases with the increase of offline unit waiting for time cost for different service strategies in public hospitals, and some patients will turn to online service channels for telemedicine services. Public hospitals increase service capacity investment in offline service channels, and the waiting time in offline service channels will decrease. As the online waiting time cost increases, the total system cost under the offline service strategy remains the same, while the total system cost under the Gatekeeper service strategy increases linearly and the total system cost under the dual-channel service strategy grows slowly. When online waiting time cost increases to a certain value, the total system cost under the Gatekeeper service strategy will be much higher than that under the dual-channel service strategy and the offline service strategy. The conditions for the gatekeeper service strategy are relatively strict, and healthcare service system planners should choose carefully considering the real situation.

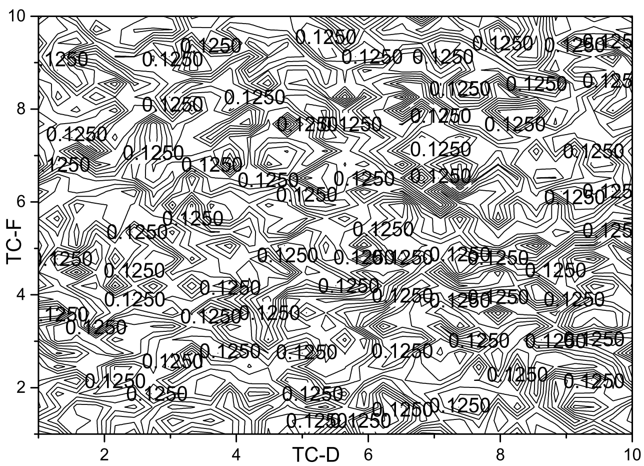

FIGURE 10. Impact of patient online and offline delays sensitivity on total system cost.

Patients are free to engage in other activities while waiting in the online service channel, thus the cost per unit time waiting online is usually smaller than the cost per unit time of waiting offline. Both the gatekeeper service strategy and the dual-channel service strategy will have lower total costs than the offline service strategy. For chronic patients, time is not a major influence on patient choice behavior, and both online waiting time costs and offline waiting time costs are lower. However, Figure 10 reflects the relative change in the cost of offline or online waiting time, with the dual-channel service strategy being the optimal strategy. Most chronic diseases require long-term but uncomplicated follow-up visits with relatively low patient waiting time sensitivity, and thus governments and healthcare organizations can implement

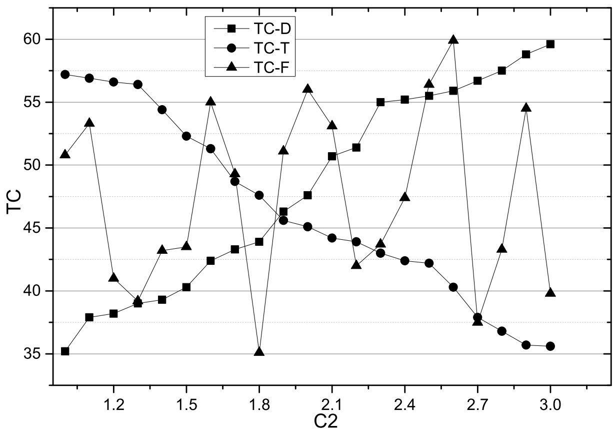

FIGURE 11. **Impact of online and offline unit service capacity costs on total system costs.**

telemedicine dual-channel services for chronic diseases, post-operative recovery and prognosis, and geriatric care first.

C. ARTIFICIAL INTELLIGENCE ASSISTED TELEMEDICINE HEALTH ANALYSIS SYSTEM UNIT SERVICE CAPACITY COST OPTIMIZATION

Public hospitals improve their offline and online service capacity will also incur corresponding service capacity investment costs, as can be seen from Figure 11, the optimal strategy changes from an offline service strategy to a dual-channel service strategy as the cost per unit of service capacity of the offline service channel increases or the cost per unit of service capacity of the online service channel decreases. The total cost of the gatekeeper service strategy is first lower than the same as the dual-channel service strategy, and finally the same as the total cost of the healthcare delivery system under the dual-channel service strategy. Because the labor cost of GPs in telemedicine is often lower than the labor cost of specialists in offline public hospitals, and because telemedicine makes full use of free medical resources, it also reduces its medical service cost. As a result, online unit service capacity costs are generally lower than offline unit service capacity costs. When the cost of online service capacity is relatively low, it will promote the adoption of telemedicine services in public hospitals.

In this study, online and offline service capabilities can be substituted for each other, only the cost per service capability is different and the misdiagnosis rate also differs. The service capacity substitution phenomenon is very common in the service field, where service providers have two or more service capacities for different service demands in the market, and when one service capacity is in shortage, another service capacity can be temporarily called to meet customer demand, for example, the substitution between luxury and regular class seats in airlines, and between luxury and regular rooms in hotels. However, there are differences in service quality and functions between service capabilities to meet different service needs, for example, the incomplete substitution between online and offline service capabilities in medical institutions, and this incomplete substitution makes the decision-making problem of medical institutions more complicated. The complexity of this problem is further exacerbated when online and offline healthcare services are provided by different providers.

VI. CONCLUSION

In terms of health IoT architecture, we propose a cloud convergence health IoT architecture, which integrates health cloud platform and sensing layer deeply by integrating various communication technologies to optimize the user experience and make health IoT applications more closely connected with people. The whole architecture consists of the health IoT perception layer, transmission layer, and health cloud service layer. The health cloud service layer consists of health cloud service support sub-layer and health cloud service application sub-layer. The hierarchy and components of the architecture are described in detail. A typical architecture of cloud-converged health IoT for specific applications is given. In the health IoT perception layer signal acquisition, the basic concepts and main components of multi-modal sensing information acquisition are introduced, a cloud robot platform for health monitoring, robot-based multimodal data sensing and aggregation, and high comfort sustainable physiological signal acquisition based on smart clothes are designed and implemented.

In terms of QoS for health IoT based on human LAN, this paper proposes a multi-level QoS framework based on the analysis of QoS requirements for health IoT using IEEE beacon model and tree routing based on tree topology to divide the transmission of health data into three different levels and ensure the priority transmission of critical data. It is fully compatible with existing communication protocols while ensuring the achievement of QoS objectives. QoS is implemented based on a tree topology, which is more suitable for large networks than a star structure. The router nodes dynamically and adaptively adjust the priority level according to the end nodes, which guarantees the overall priority transmission of router sub-node data. In health IoT emotional perception and emotional interaction, human emotional states are identified using smart device signals. The robot-based emotional interaction is achieved using a migration learning algorithm to label emotional data, a continuous conditional random field is used to separately identify emotions from data collected based on smart devices, and finally a decision layer artificial intelligence algorithm is fused for emotional classification and prediction. The feasibility of the proposed approach is verified by the implemented sentiment interaction demonstration application. The optimal strategy for public hospitals is to spend all government financial subsidies on service capacity investments, and their service capacity decisions are not influenced by the service price and service capacity decisions of third-party telemedicine providers, and the interaction between public hospitals and third-party telemedicine providers is unidirectional. Second, government subsidies to public hospitals can increase the total patient utility of offline service channels and reduce the waiting time of offline service channels, and also increase the profits of third-party telemedicine providers, but its impact diminishes as the government subsidy budget increases, and when the government subsidy budget exceeds a certain value, the price of telemedicine services subsequently increases, which will be detrimental to the popularity of telemedicine services. In the future, we will further optimize and improve based on this conclusion. In the future, we will further optimize and design the model on the basis of existing research, and finally it can be applied to the market.

REFERENCES

[1] Q. Wu, Y. Qiao, R. Guo, S. Naveed, T. Hirtz, X. Li, Y. Fu, Y. Wei, G. Deng, Y. Yang, X. Wu, and T.-L. Ren, "Triode-mimicking graphene pressure sensor with positive resistance variation for physiology and motion monitoring," *ACS Nano*, vol. 14, no. 8, pp. 10104–10114, Jul. 2020.

[2] S. Betti, R. M. Lova, E. Rovini, G. Acerbi, L. Santarelli, M. Cabiati, S. D. Ry, and F. Cavallo, "Evaluation of an integrated system of wearable physiological sensors for stress monitoring in working environments by using biological markers," *IEEE Trans. Biomed. Eng.*, vol. 65, no. 8, pp. 1748–1758, Aug. 2018.

[3] D. R. Seshadri, R. T. Li, J. E. Voos, J. R. Rowbottom, C. M. Alfes, C. A. Zorman, and C. K. Drummond, "Wearable sensors for monitoring the physiological and biochemical profile of the athlete," *NPJ Digit. Med.*, vol. 2, no. 1, pp. 1–6, Jul. 2019.

[4] A. Aliverti, "Wearable technology: Role in respiratory health and disease," *Breathe*, vol. 13, no. 2, pp. e27–e36, Jun. 2017.

[5] S. P. Wright, T. S. H. Brown, S. R. Collier, and K. Sandberg, "How consumer physical activity monitors could transform human physiology research," *Amer. J. Physiol.-Regulatory, Integrative Comparative Physiol.*, vol. 312, no. 3, pp. R358–R367, Mar. 2017.

[6] S. Chakraborty, V. Bhatt, and T. Chakravorty, "Big-data, IoT wearable and mHealth cloud platform integration triads—A logical way to patient-health monitoring," *Int. J. Eng. Adv. Technol.*, vol. 9, no. 3, pp. 388–394, Mar. 2020.

[7] A. Muneer, S. M. Fati, and S. Fuddah, "Smart health monitoring system using IoT based smart fitness mirror," *Telkomnika*, vol. 18, no. 1, pp. 317–331, Feb. 2020.

[8] U. Satija, B. Ramkumar, and M. Sabarimalai Manikandan, "Real-time signal quality-aware ECG telemetry system for IoT-based health care monitoring," *IEEE Internet Things J.*, vol. 4, no. 3, pp. 815–823, Jun. 2017.

[9] J. Vanrenterghem, N. J. Nedergaard, M. A. Robinson, and B. Drust, "Training load monitoring in team sports: A novel framework separating physiological and biomechanical load-adaptation pathways," *Sports Med.*, vol. 47, no. 11, pp. 2135–2142, Nov. 2017.

[10] J. Triloka, S. M. N. A. Senanayake, and D. Lai, "Neural computing for walking gait pattern identification based on multi-sensor data fusion of lower limb muscles," *Neural Comput. Appl.*, vol. 28, no. S1, pp. 65–77, Dec. 2017.

[11] G. Giorgi, A. Galli, and C. Narduzzi, "Smartphone-based IOT systems for personal health monitoring," *IEEE Instrum. Meas. Mag.*, vol. 23, no. 4, pp. 41–47, Jun. 2020.

[12] P. K. Gupta, B. T. Maharaj, and R. Malekian, "A novel and secure IoT based cloud centric architecture to perform predictive analysis of users activities in sustainable health centres," *Multimedia Tools Appl.*, vol. 76, no. 18, pp. 18489–18512, Sep. 2017.

[13] S. Khan, S. Parkinson, L. Grant, N. Liu, and S. Mcguire, "Biometric systems utilising health data from wearable devices: Applications and future challenges in computer security," *ACM Comput. Surveys*, vol. 53, no. 4, pp. 1–29, Sep. 2020.

[14] M. Guo, Z. Wang, N. Yang, Z. Li, and T. An, "A multisensor multiclassifier hierarchical fusion model based on entropy weight for human activity recognition using wearable inertial sensors," *IEEE Trans. Human-Mach. Syst.*, vol. 49, no. 1, pp. 105–111, Feb. 2019.

[15] M. K. Hassan, A. I. El Desouky, M. M. Badawy, A. M. Sarhan, M. Elhoseny, and M. Gunasekaran, "EoT-driven hybrid ambient assisted living framework with naïve Bayes–firefly algorithm," *Neural Comput. Appl.*, vol. 31, no. 5, pp. 1275–1300, May 2019.

[16] O. Boursalie, R. Samavi, and T. E. Doyle, "Machine learning and mobile health monitoring platforms: A case study on research and implementation challenges," *J. Healthcare Informat. Res.*, vol. 2, nos. 1–2, pp. 179–203, Jun. 2018.

[17] J. C. Goldsack, A. Coravos, J. P. Bakker, B. Bent, A. V. Dowling, C. Fitzer-Attas, A. Godfrey, J. G. Godino, N. Gujar, E. Izmailova, C. Manta, B. Peterson, B. Vandendriessche, W. A. Wood, K. W. Wang, and J. Dunn, "Verification, analytical validation, and clinical validation (V3): The foundation of determining fit-for-purpose for biometric monitoring technologies (BioMeTs)," *NPJ Digit. Med.*, vol. 3, no. 1, pp. 1–5, Apr. 2020.

[18] D. Z. H. Levett, S. Jack, M. Swart, J. Carlisle, J. Wilson, C. Snowden, M. Riley, G. Danjoux, S. A. Ward, P. Older, and M. P. W. Grocott, "Perioperative cardiopulmonary exercise testing (CPET): Consensus clinical guidelines on indications, organization, conduct, and physiological interpretation," *Brit. J. Anaesthesia*, vol. 120, no. 3, pp. 484–500, Mar. 2018.

[19] T. Yang, X. Jiang, Y. Zhong, X. Zhao, S. Lin, J. Li, X. Li, J. Xu, Z. Li, and H. Zhu, "A wearable and highly sensitive graphene strain sensor for precise home-based pulse wave monitoring," *ACS Sensors*, vol. 2, no. 7, pp. 967–974, Jul. 2017.

[20] A. Li, M. C. Riddell, D. Potashner, R. E. Brown, and R. Aronson, "Time lag and accuracy of continuous glucose monitoring during high intensity interval training in adults with type 1 diabetes," *Diabetes Technol. Therapeutics*, vol. 21, no. 5, pp. 286–294, May 2019.

[21] K. E. Friedl, "Military applications of soldier physiological monitoring," *J. Sci. Med. Sport*, vol. 21, no. 11, pp. 1147–1153, Nov. 2018.

[22] N. Dey, A. S. Ashour, F. Shi, S. J. Fong, and R. S. Sherratt, "Developing residential wireless sensor networks for ECG healthcare monitoring," *IEEE Trans. Consum. Electron.*, vol. 63, no. 4, pp. 442–449, Nov. 2017.

[23] A. Sheth, U. Jaimini, and H. Y. Yip, "How will the Internet of Things enable augmented personalized health?" *IEEE Intell. Syst.*, vol. 33, no. 1, pp. 89–97, Jan. 2018.

[24] W. Wu, S. Pirbhulal, H. Zhang, and S. C. Mukhopadhyay, "Quantitative assessment for self-tracking of acute stress based on triangulation principle in a wearable sensor system," *IEEE J. Biomed. Health Informat.*, vol. 23, no. 2, pp. 703–713, Mar. 2019.

[25] B. Xu, L. Li, D. Hu, B. Wu, C. Ye, and H. Cai, "Healthcare data analysis system for regional medical union in smart city," *J. Manage. Anal.*, vol. 5, no. 4, pp. 334–349, Oct. 2018.

[26] M. Chen, Y. Ma, J. Song, C.-F. Lai, and B. Hu, "Smart clothing: Connecting human with clouds and big data for sustainable health monitoring," *Mobile Netw. Appl.*, vol. 21, no. 5, pp. 825–845, Oct. 2016.

[27] M. Chen, Y. Ma, Y. Li, D. Wu, Y. Zhang, and C. H. Youn, "Wearable 2.0: Enabling human-cloud integration in next generation healthcare systems," *IEEE Commun. Mag.*, vol. 55, no. 1, pp. 54–61, Jan. 2017.

[28] C. Barbosa Pereira, X. Yu, M. Czaplik, V. Blazek, B. Venema, and S. Leonhardt, "Estimation of breathing rate in thermal imaging videos: A pilot study on healthy human subjects," *J. Clin. Monitor. Comput.*, vol. 31, no. 6, pp. 1241–1254, Dec. 2017.

[29] H. Xu, P. Li, Z. Yang, X. Liu, Z. Wang, W. Yan, M. He, W. Chu, Y. She, Y. Li, D. Cao, M. Yan, and Z. Zhang, "Construction and application of a medical-grade wireless monitoring system for physiological signals at general wards," *J. Med. Syst.*, vol. 44, no. 10, pp. 1–5, Oct. 2020.

[30] A. Karsaz, "Chattering-free hybrid adaptive neuro-fuzzy inference system-particle swarm optimisation data fusion-based BG-level control," *IET Syst. Biol.*, vol. 14, no. 1, pp. 31–38, Feb. 2020.

[31] M. Jacob Rodrigues, O. Postolache, and F. Cercas, "Physiological and behavior monitoring systems for smart healthcare environments: A review," *Sensors*, vol. 20, no. 8, p. 2186, Apr. 2020.

[32] J. Chen, W. Wang, Y. Zhou, S. H. Ahmed, and W. Wei, "Exploiting 5G and blockchain for medical applications of drones," *IEEE Netw.*, vol. 35, no. 1, pp. 30–36, Jan. 2021.

[33] W. Wang, Z. Gong, J. Ren, F. Xia, Z. Lv, and W. Wei, "Venue topic model–enhanced joint graph modelling for citation recommendation in scholarly big data," *ACM Trans. Asian Low-Resource Lang. Inf. Process.*, vol. 20, no. 1, pp. 1–15, Apr. 2021.

[34] W. Wei, Q. Ke, J. Nowak, M. Korytkowski, R. Scherer, and M. Woźniak, "Accurate and fast URL phishing detector: A convolutional neural network approach," *Comput. Netw.*, vol. 178, Sep. 2020, Art. no. 107275.

[35] S. Qi, Y. Lu, W. Wei, and X. Chen, "Efficient data access control with fine-grained data protection in cloud-assisted IIoT," *IEEE Internet Things J.*, vol. 8, no. 4, pp. 2886–2899, Feb. 2021.
[36] F. Orujov, R. Maskeliūnas, R. Damaševičius, and W. Wei, "Fuzzy based image edge detection algorithm for blood vessel detection in retinal images," *Appl. Soft Comput.*, vol. 94, Sep. 2020, Art. no. 106452.
[37] Q. Ke, J. Zhang, W. Wei, D. Połap, M. Woźniak, L. Kośmider, and R. Damaševičius, "A neuro-heuristic approach for recognition of lung diseases from X-ray images," *Expert Syst. Appl.*, vol. 126, pp. 218–232, Jul. 2019.

HENG YU was born in Henan, China, in 1984. He received the bachelor's and master's degrees from Henan University, in 2008 and 2011, respectively. He is currently working as a Lecturer with the School of Information Engineering, Pingdingshan University. He has published nine articles, one of which has been indexed by EI. His research interests include digital image processing, machine learning and the Internet of Things.

ZHIQING ZHOU was born in Zhejiang, China, in 1978. He received the bachelor's and master's degrees from Central China Normal University, in 2002 and 2007, respectively. He is currently working as a Lecturer with the School of Information Engineering, Pingdingshan University. His research interests include the Internet of Things and machine vision.