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Maximizing Efficiency in Telemedicine: An IoT-Based Artificial Intelligence Optimization Framework for Health Analysis

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ABSTRACT

This paper delves into a comprehensive exploration of health IoT architecture and its implementation technologies, considering both theoretical and practical aspects. The study emphasizes the theoretical importance and practical applicability of the research. Key areas covered include cloud fusion health IoT architecture, multimodal information acquisition within the health IoT perception layer, multi-level service quality assurance based on human LAN in health IoT, and emotional perception and interaction within the health IoT context. In terms of health IoT architecture, the proposal introduces a cloud-converged approach that deeply integrates the health cloud platform and perception layer. This integration involves utilizing various communication technologies to enhance user experience, fostering closer connections between health IoT applications and individuals. The paper details basic concepts and main components of multimodal sensing information collection, outlining the design and implementation of a health monitoring cloud robotics platform. This platform involves robotics-based multimodal data sensing and aggregation, as well as the collection of comfortable and sustainable physiological signals through smart clothing. The feasibility and performance of the Quality of Service (QoS) framework proposed in this paper are validated through computer simulations. Migration learning is employed for emotion data labeling, and continuous conditional random fields are utilized for emotion identification based on data from smartphones and smart clothing. The paper concludes with decision layer fusion for emotion classification prediction.

Keywords: Internet of things, artificial intelligence, telemedicine, health monitoring, data analysis

SECTION I: INTRODUCTION

In the past decade, IoT technology has rapidly evolved from theoretical research to practical deployment, yielding numerous representative applications in various fields (Wu et al., 2020). Currently, IoT is expanding and integrating early coordination networks and RFID applications into different levels of national economic and social life. The emergence of new application scenarios and demands is raising higher requirements for traditional IoT (Betti et al., 2017). Simultaneously, the Internet of Things, being a multidisciplinary field encompassing sensors, microelectronics, computers, communications, and more, is confronted with unprecedented technical challenges. The "people-oriented" health IoT concept places increased emphasis on quality of service (QoS) and quality of experience (QoE) as vital evaluation indicators. Effectively applying the latest technologies to enhance the service level of health IoT has become a pressing technical challenge (Seshadri et al., 2019; Aliverti, 2017). Telehealth monitoring service integrates healthcare resources, extending coverage beyond

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institutions. Essentially, it functions as a telemedicine health digital system for communities, families, and convalescent or rehabilitation institutions, catering to a broad range of individuals (Wright et al., 2017). Service targets for telehealth monitoring encompass a wide range, including injured individuals in disasters, maternity cases, newborns, elderly patients, disabled individuals, chronic disease patients, emergency cases, and those in a sub-healthy state. Its applications span the study of human physiological states under extreme conditions, the advancement of emergency medicine, and the enhancement of medical services in remote areas and family healthcare for numerous families, challenging and reshaping the current medical service paradigm (Chakraborty, Bhatt, & Chakravorty, 2020). Telehealth monitoring is poised to enhance the doctor-patient relationship, expand service reach, optimize medical resource utilization, improve access to quality resources, decrease overall medical and health service costs, and deliver timely medical and health protection (Muneer, Fati, & Fuddah, 2020). As technology matures and application demand grows, IoT is gaining significant attention in the health services sector. The widespread use of mobile communication devices in recent years has created a substantial market space for the healthcare industry (Satija, Ramkumar, & Manikandan, 2017). Despite this, there are limited successful applications leveraging IoT technology to deliver health services to families and individuals, offering personalized health services. Health IoT represents a crucial branch of IoT applications, and the transformative shift it brings to the health service model stands to benefit a broad user base while also fostering the development of the health service industry (Vanrenterghem et al., 2017; Triloka, Senanayake, & Lai, 2017). Presently, there are notable IoT applications in the medical industry, spanning health monitoring, sports promotion, and spiritual comfort. The swift integration of IoT technology with traditional medical information systems has led to a growing focus on clinical medical applications based on wireless networks due to their speed, convenience, and anticipated future development trends (Giorgi, Galli, & Narduzzi, 2020). In the era of mobile medical care, IoT-based medical information technology has advanced significantly. Doctors now utilize mobile clinical terminals to perform nearly all medical tasks, substantially enhancing efficiency and delivering improved diagnosis and treatment services for patients. Figure 1 illustrates the typical architecture of health IoT in the medical industry, showcasing how IoT integrates and optimizes hospital resources to enhance service efficiency (Gupta, Maharaj, & Malekian, 2017). Because of its high degree of specialization and challenging implementation, this type of IoT application in the medical industry is limited to adoption within professional medical institutions and is not suitable for the general population (Khan et al., 2020).

The home-based remote health monitoring application integrates physiological signal sensors, wireless communication technology, and cloud computing. This overturns the traditional health monitoring model and emerges as a crucial branch in the development of health IoT (Guo et al., 2018). 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 (Hassan et al., 2019; Boursalie, Samavi, & Doyle, 2018). This application is especially well-suited for the elderly, chronic disease patients, and those in a sub-healthy state. Utilizing advanced mobile, portable, and low-power intelligent health sensing devices, it can detect various physiological indicators such as blood oxygen, pulse rate, blood pressure, blood sugar, bone density, Electrocardiograph (ECG), body temperature, respiration, etc. (Goldsack et al., 2020; Levett et al., 2018). The health monitoring service model is bifurcated into two types: family-based monitoring and community-based monitoring. Community-based health monitoring systems link patients with medical and health experts using physiological signal sensing devices, wireless communication, and a cloud-based health service platform. This facilitates medical professionals in comprehending users' physiological indicators and offering guidance on disease treatment and health plans (Yang et al., 2017).

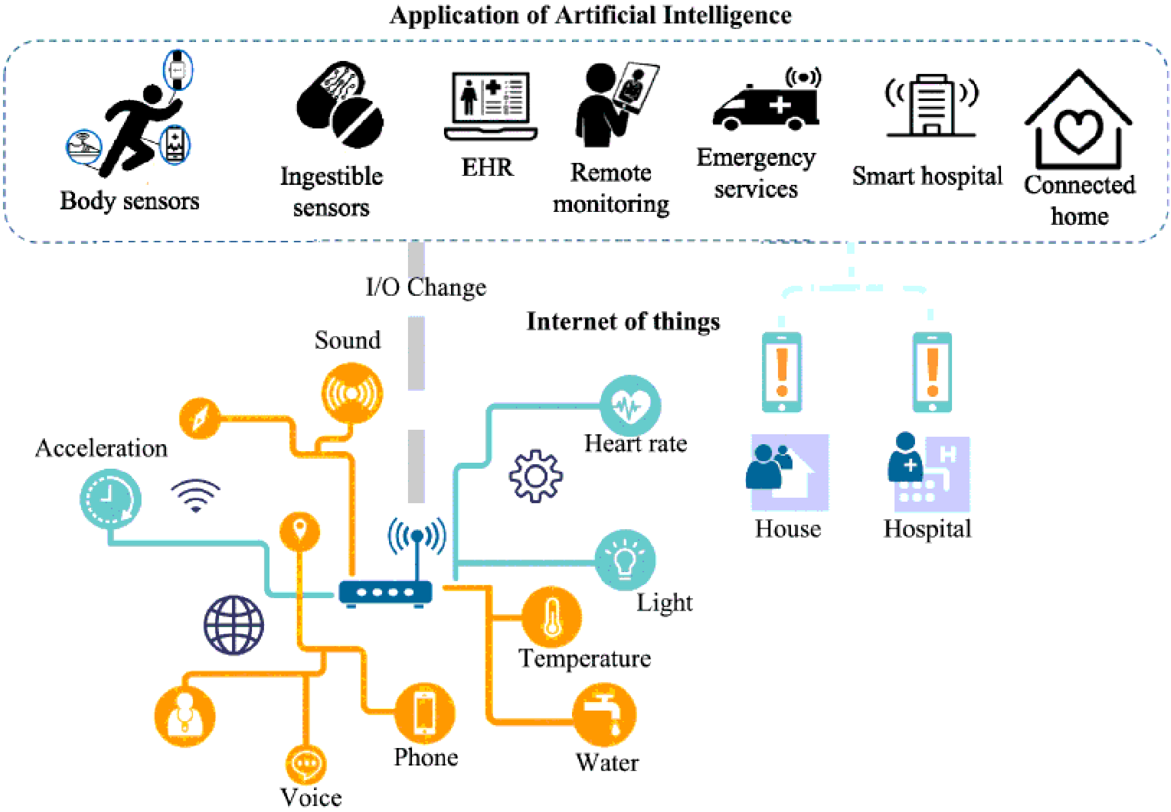

Figure 1. Health IoT architecture for the healthcare industry

In contrast, the architecture of a home-based health monitoring system is relatively simple, typically necessitating only the purchase of a dedicated health-aware device for usage (Li et al., 2019). These devices typically connect to smartphones via Bluetooth, transferring the detected physiological data to the mobile device. Users can then view test results and save historical data in real-time through a dedicated health application installed on the smartphone. Some device manufacturers also offer value-added services, such as uploading data to cloud servers, querying historical data, and providing personalized health guidance (Friedl, 2018). Continuous monitoring of physiological indicators categorizes health monitoring into two types: continuous monitoring and intermittent monitoring. Certain specialized physiological indicators require continuous monitoring to identify abnormalities (Dey et al., 2017). The paper introduces a cloud-converged health IoT architecture, which involves a deep integration of the health cloud platform with the sensing layer. This integration utilizes multiple communication technologies to optimize user experience and establish a closer connection between health IoT applications and individuals (Sheth, Jaimini, & Yip, 2018; Wu et al., 2018; Xu et al., 2018). The entire architecture comprises the health IoT perception layer, transmission layer, and health cloud service layer. Within the health cloud service layer, there are two sub-layers: health cloud service support and health cloud service application. The paper thoroughly describes the hierarchy and components of the architecture, providing a detailed overview. It includes a typical cloud-converged health IoT architecture for specific applications. The paper also covers basic concepts and main components of multimodal sensing information acquisition, the design and implementation of a cloud robotics platform for health monitoring, robotics-based multimodal data sensing and aggregation, and the acquisition of high-comfort sustainable physiological signals based on smart clothing. To verify the feasibility of the designed health monitoring system and assess its performance indicators, relevant underlying hardware systems, embedded software, and upper-layer health application software are developed using a real hardware and software platform (Barbosa Pereira et al., 2017). Additionally, the paper conducts a thorough analysis of quality-of-service assurance requirements in health IoT and suggests a framework based on a multi-level priority policy. To validate the feasibility and assess the performance metrics of this framework, a custom simulation model is created using a network simulation platform. Experimental results demonstrate that the proposed framework effectively meets the diverse and performance-related quality-of-service assurance requirements of health IoT.

SECTION II: ENHANCING HEALTH IOT ARCHITECTURE THROUGH CLOUD-CONVERGED ARTIFICIAL INTELLIGENCE

Strategic Design of Health IoT Architecture with Artificial Intelligence

The health IoT perception layer aims to gather raw signals from the external environment using various sensors and collect diverse physiological signals related to human health (Chen et al., 2016).

The perception layer typically involves preprocessing raw signals for efficient transmission of sensory data. Additionally, short-range wireless communication plays a crucial role in transmitting the collected data to the upper layers (Chen et al., 2017).

In health IoT, where people are the primary targets for signal acquisition and service recipients, the human local area network holds particular significance within the perception layer (Barbosa Pereira et al., 2017). In complex signal acquisition scenarios, the coordination of multiple sensing nodes is essential, and their collaborative communication relies on short-range wireless technologies in the sensing layer. The primary challenges involve sensor technology, node security, embedded operating systems, and multi-protocol gateways. This paper introduces a three-layer architecture for health IoT with cloud convergence, encompassing the health IoT sensing layer, health IoT transmission layer, and health cloud service layer (Xu et al., 2020). The health cloud service layer is subdivided into the cloud service support sub-layer and the cloud service application sub-layer, illustrated in Figure 2. The functions and components of each layer are briefly described below.

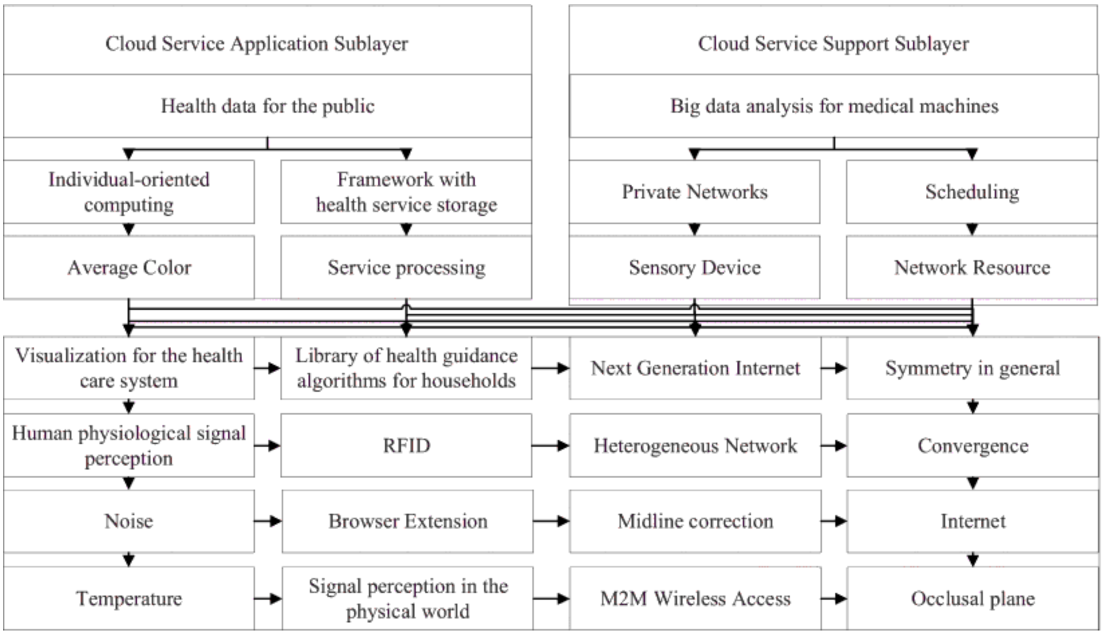

Figure 2. Health IoT architecture for cloud convergence

Wearable devices have emerged as a crucial means of gathering physiological data at the sensory level in health IoT. These devices primarily capture various physiological parameters from the human body, such as EEG, ECG, blood pressure, blood oxygen, respiration, electromyography, and other signals. Positioned in close contact with the human body, wearable devices can be worn or implanted in the epidermis, facilitating the collection, conditioning, amplification, and quantification of physiological signals. The quantified data is then wirelessly transmitted to external network communication access equipment. Given the potential use of multiple wearable devices simultaneously, addressing possible mutual interference and establishing data transmission priorities are vital technical challenges in the health IoT sensing layer. The paper proposes traditional wearable device signal acquisition devices and introduces physiological signal acquisition based on smart clothes. In this paper, we propose the utilization of wearable smart clothes for gathering human physiological signals in the health IoT sensing layer. Various miniature physiological signal acquisition sensors are integrated into the smart set to enable the acquisition of multimodal physiological signals. Bioelectrical signals in the human body serve as crucial indicators of vital signs, and disease diagnosis and health condition assessment typically involve obtaining various bioelectrical signals. Chapter 2 discusses the significance of electrodes in bioelectric signal acquisition, and in recent years, textile-structured electrodes have made notable advancements in fabrication processes and lifetimes. The use of textile-structured electrodes for measuring and monitoring human bioelectric signals has garnered widespread attention, as discussed in Chapter 3. The paper suggests employing textile dry electrodes for sensing electrical signals, and integrating them into clothing. This innovation overcomes psychological discomfort for users, enhancing comfort and enabling bioelectrical signal monitoring anytime and anywhere (Chapter 4). Textile electrodes, in contrast to traditional disposable ones, offer advantages such as softness, breathability, moisture permeability, washability, and extended dry-state use without causing skin irritation—ideal for prolonged usage (Chen et al., 2021). Wisdom clothing is capable of collecting diverse human physiological signals, exemplified here by human ECG signals, respiratory signals, heart rate, and oxygen saturation. The technology relies on washable textile dry electrodes, allowing users to monitor these physiological signals by wearing the wisdom garment. The collected signals can be utilized for applications such as disease diagnosis and health condition assessment (Chapter 5).

Designing the Transport Layer and AI-Cloud Service Layer for Health IoT

Semantic understanding and knowledge representation of multimodal data enhance the intelligent perception and comprehension of real-world scenarios. This capability supports various industry applications, including intelligent Q&A, dialogue systems, human-computer interaction, and recommendations. The health IoT transport layer functions as a conduit between upper and lower layers, facilitating the transmission of control commands from upper-layer applications to sensing nodes through IoT gateways. It also receives data collected from the sensing layer, utilizing various network technologies to transmit data to upper-layer applications and interface with them (Wang et al., 2020; Wei et al., 2020; Qi et al., 2020; Orujov et al., 2020). The transport layer encounters challenges in converging existing networks with perception layer networks. The disparity in protocol design and communication mechanisms poses a significant hurdle for achieving network interconnection and interoperability. While current solutions involve multi-protocol gateways, the increasing complexity of network technologies and specifications, coupled with rapid updates, makes IoT gateway development challenging. Consequently, finding a universal solution remains difficult (Ke et al., 2019).

The scope of health IoT varies widely, encompassing both large-scale deployments covering extensive areas and small-scale implementations focused on individual units.

Consequently, the network technologies and communication requirements differ significantly. Developing multi-network convergence technology tailored to the specific needs of health IoT poses a major technical challenge. Existing network technologies, designed within the constraints of their era's technical background and application requirements, exhibit serious deficiencies in scalability and other aspects (Rasool, Ghafoor, & Fareed, 2021). Additionally, these networks, operational for many years with significant equipment investments, often prioritize profit by withholding technical details. This lack of transparency seriously impedes technological innovation and hinders the ability to swiftly adapt to the pressing need for network technology changes, especially in emerging applications like IoT. Therefore, conducting innovative research on network technologies for emerging health IoT applications is a challenging task, given the need to ensure the normal operation of existing networks and protect initial investments. The cloud service support sub-layer compresses, stores, and analyzes physical world and human physiological data, providing crucial support for upper-layer health IoT services. In response to the growing data from IoT-connected devices, this layer relies on cloud computing technology and massively parallel computing clusters for real-time processing and advanced analytics. The analytics layer, in large IoT architectures, utilizes resource pools based on virtualization technology to dynamically allocate resources for optimal utilization. Addressing the challenges posed by the large volume of unstructured data generated by IoT is crucial. Despite advances in sensor research driving home health monitoring, this paper proposes a cloud-fused health monitoring system architecture, integrating mobile robots, cloud computing, and big data technology to meet the demands of fast access and efficient processing in health monitoring.

Comprehensive Design of Telemedicine Health Analysis System Integrating IoT and AI

The telemedicine system manages IoT gateways for registration, login, and data release. It receives medical monitoring data, and decodes and analyzes fat, blood glucose, blood pressure, oxygen saturation, and ECG data, storing it in a database. Users and health professionals can log in to view real-time medical data. The system comprises three subsystems: basic platform (manages IoT gateways and database), application platform (provides user login and displays medical data), and specific application (offers various functions). The wavelet transform is employed for signal representation.

SECTION III: ANALYSIS AND PERCEPTION IN AN ARTIFICIAL INTELLIGENCE-ASSISTED TELEMEDICINE HEALTH INFORMATION ACQUISITION SYSTEM

Multimodal Information Acquisition in the Health IoT Perception Layer

This paper introduces a mobile robotics architecture designed around 5G-ATE technology, incorporating cloud computing and big data. The scalable architecture is adaptable to various robotics applications. The proposed system, featuring emotion recognition and feedback, enhances robot intelligence and user experience. Key components include a humanoid robot, a 5G-LTE network, an intelligent control terminal supporting LTE communication, and a cloud platform. The paper emphasizes the development trends in robotics, focusing on the integration of 5G-LTE, cloud computing, big data, and machine learning for an intelligent mobile cloud robot system, as shown in Figure 3.

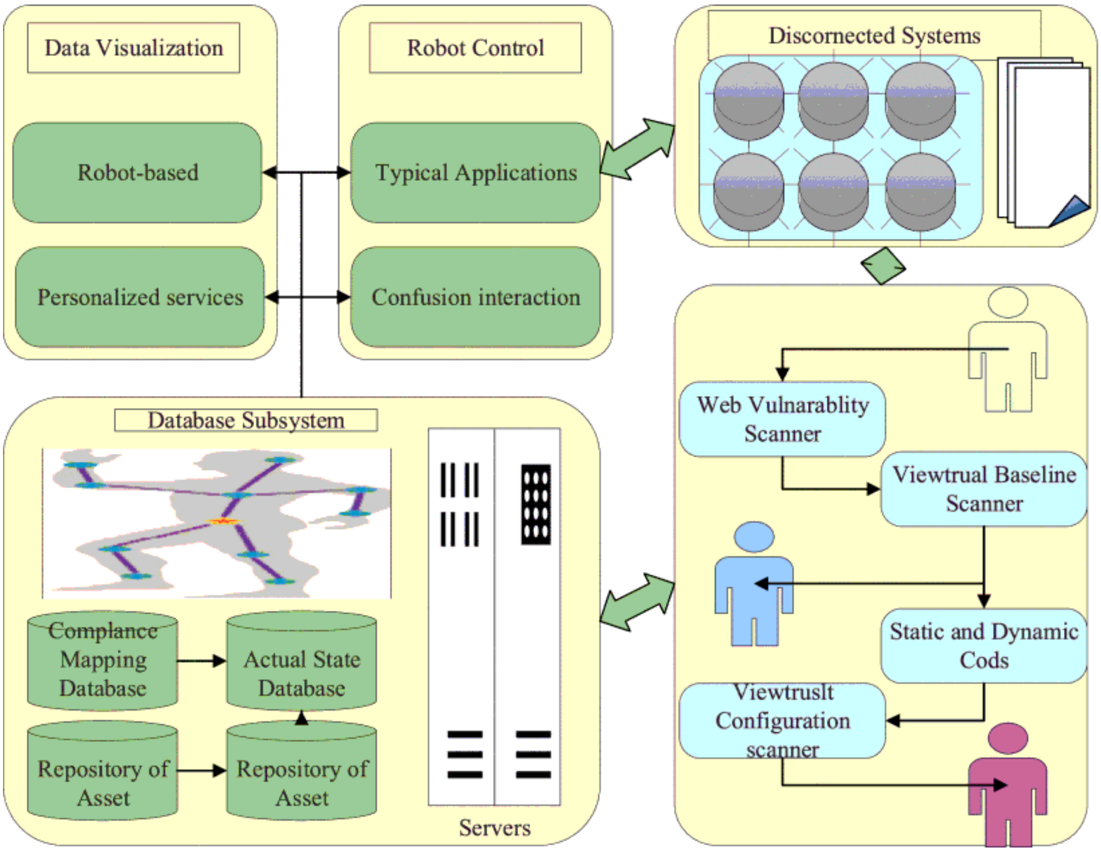

Figure 3. LTE-based mobile cloud robot architecture

Implementation of Telemedicine Health Analysis System: Applications and Perceptions

This paper discusses the development of robot-related application software based on the Android platform. It focuses on the implementation of the robot's remote control software, covering functional modules such as UI, robot control, voice recognition, sensor data processing, display, and remote video transmission. The user interface module facilitates interaction and remote communication, incorporating buttons for network connection, voice control, video transmission, and more. The robot control module enables remote control through the user's LTE mobile smart terminal or the cloud platform. Voice recognition integrates offline and cloud-based recognition for user-robot interaction. Real-time video transmission utilizes the UDP protocol with control and compression modules to ensure efficiency. The paper presents an LTE-based mobile robot architecture using humanoid robots, detailing components and demonstrating emotional interaction implementation to validate feasibility and scalability.

Intelligent Fusion of Multimodal Sensing Data using Artificial Intelligence

The robot's data acquisition involves a microcontroller and main controller, collecting physiological and environmental data. Sensors include temperature, humidity, and body sensors for health metrics. Aggregated data is sent to a cloud platform for storage and analysis. The robot controller uses a 32-bit ARM processor with Android OS. A mobile device with Android platform controls the hardware, enabling remote control, real-time video transmission, and health monitoring. The system integrates emergency response, voice recognition, and synthesis. The feasibility is verified through real hardware platform development. The testing system achieves the collection and aggregation of environmental data (temperature, humidity, harmful gases) and human physiological signals (heart rate, blood pressure). See Figure 4 for data collection and aggregation operations.

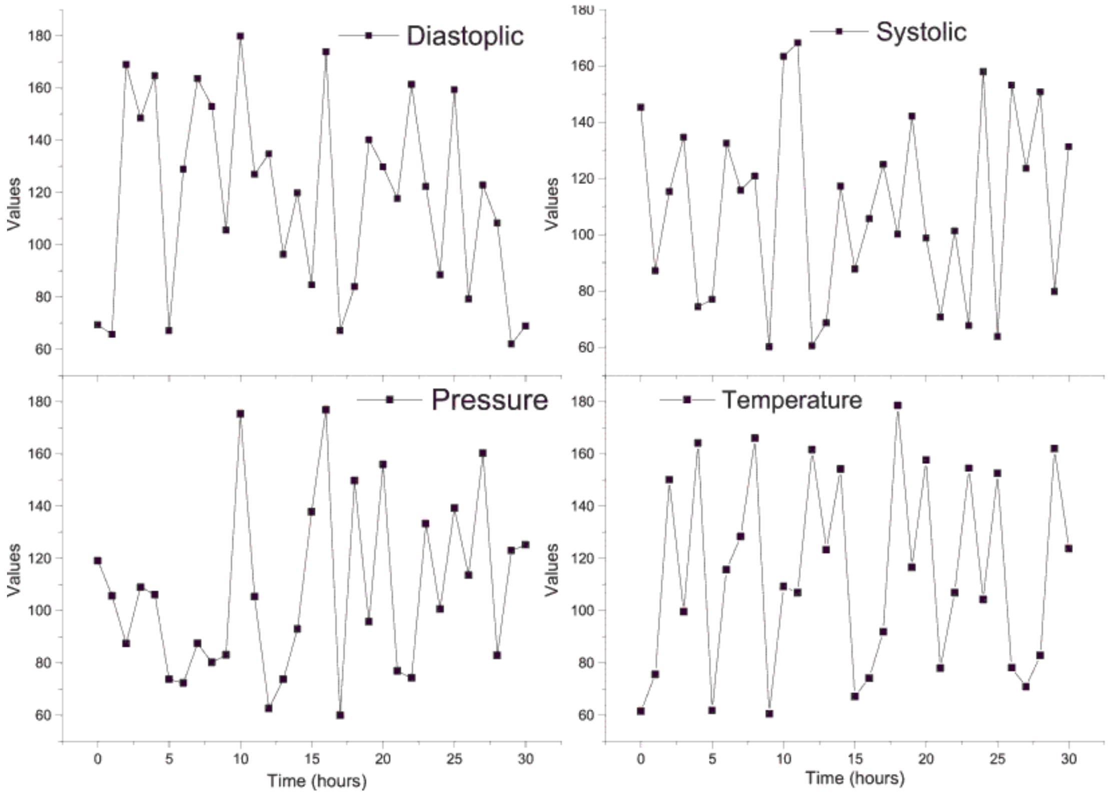

Figure 4. Multimodal sensing data aggregation

Remote IoT Human Data Gathering, Analysis, and Processing

The summary describes the importance of ECG (Electrocardiogram) in clinical medicine, its applications in diagnosing heart-related conditions and emotional analysis. The challenge lies in the portability and interference issues associated with traditional ECG measurement. Smart clothes are introduced for ECG collection, but raw signals need preprocessing to eliminate interference noise. The QRS wave group detection is crucial, involving finding the R-wave peak, and a method to filter misdirected peaks is proposed to enhance accuracy in sentiment analysis.

SECTION IV: EMOTION SENSING AND INTERACTION IN TELEMEDICINE IOT

Designing a Framework for Emotional Interaction in Telemedicine Applications

The paper introduces a novel framework for emotional interaction in telemedicine applications. The framework includes four layers: emotional information acquisition, emotional interaction control center, emotional interaction carrier, and end-user. Emotional data is acquired from health IoT perception layers, processed in the control center, and used to control emotional interaction carriers, such as health monitoring robots. Smart clothes, designed for emotion-related physiological data acquisition, enhance the framework. Cloud-based analysis of ECG data enables real-time emotion detection, with machine learning algorithms refining emotion models based on user feedback for improved accuracy over time.

Analysis and Assessment of Remote Emotion Detection Systems

The study involved dividing ECG sample data into training and test sets, extracting features, and training a classification model using a support vector machine. The sentiment prediction accuracy for 14 users varied, with some achieving over 60% accuracy, while others, like User 2 and User 7, showed lower accuracy. The accuracy for specific emotions varied, with angry at 65.74%, Fear at 53.62%, and Sadness at 49.37%. The overall accuracy fluctuated, suggesting the need for increased diversity in sentiment detection data and the exploration of new methods to enhance accuracy and stability in future research.

Analysis of Human-Emotional Interaction in Telemedicine IoT

This paper discusses the development of a pillow robot designed for emotional interaction, aiming to address the growing issue of personal loneliness in a fast-paced and increasingly isolated society. The proposed solution involves the integration of practical functionalities with the capacity to provide emotional support, emphasizing the role of robots as suitable carriers for human emotional interaction. The research includes a detailed exploration of the pillow robot's composition, emotional interaction scenarios, methods for emotional data collection and processing, as well as an emotional recognition approach based on continuous conditional random domains and decision layer fusion methods. Additionally, the paper presents a demonstration system for emotional interaction and highlights the application of telemedicine technologies in facilitating remote consultations and communication between specialists, patients, and medical staff. The accuracy and effectiveness of emotion detection are tested through a 10-day trial involving 10 volunteers, utilizing a cloud platform for real-time data analysis and interpretation. This section demonstrates a notable improvement in sentiment detection accuracy by integrating multi-source data compared to relying solely on single ECG data. The back-end cloud platform plays a crucial role in automatically adjusting the system's emotion model based on emotional state labeling information provided by volunteers. As the testing period accumulates, the system dynamically enhances emotion detection accuracy by learning from volunteers' feedback. The initial accuracy for all emotional states is relatively low, but through continuous learning and adaptation, the cloud-based emotion detection model progressively refines, reaching a stable state where further improvement becomes marginal, as shown in Figure 5.

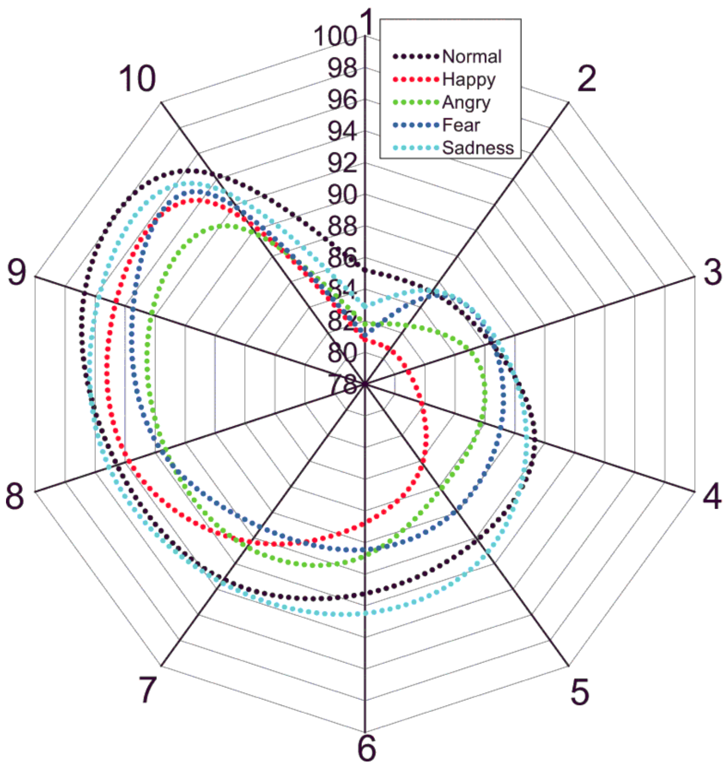

Figure 5. The trend of the accuracy of emotion detection

SECTION V: OPTIMIZING SERVICE DECISIONS IN TELEMEDICINE HEALTH ANALYSIS SYSTEMS THROUGH ARTIFICIAL INTELLIGENCE ASSISTANCE

Optimizing Referral Costs in Telemedicine Health Analysis Systems through Artificial Intelligence Assistance

This study assesses the total system cost of telemedicine health systems, focusing on key factors such as patient transportation cost, telemedicine misdiagnosis rate, waiting time cost, and service capacity cost. Utilizing patient arrival rates from reputable public hospitals, the analysis considers service strategies like Gatekeeper and Dual-channel. The research highlights the impact of unit transportation cost on the total healthcare system cost, emphasizing the influence of geographic distribution and varying demand for medical services. The findings suggest optimal service strategies based on transportation costs and medical service demands in public hospitals.

Public hospitals employ offline service strategies, and the misdiagnosis rate of telemedicine does not impact this healthcare delivery system, as illustrated in Figure 6. The total system cost increases with the misdiagnosis rate under both the Gatekeeper service strategy and dual-channel service strategy. However, under the dual-channel service strategy, the total system cost does not increase linearly with the misdiagnosis rate. At lower levels of misdiagnosis 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 opt for their initial visit through offline service channels. When the misdiagnosis rate surpasses a certain threshold, the total cost of the dual-channel service strategy increases rapidly, prompting hospitals to consider abandoning the telemedicine service channel.

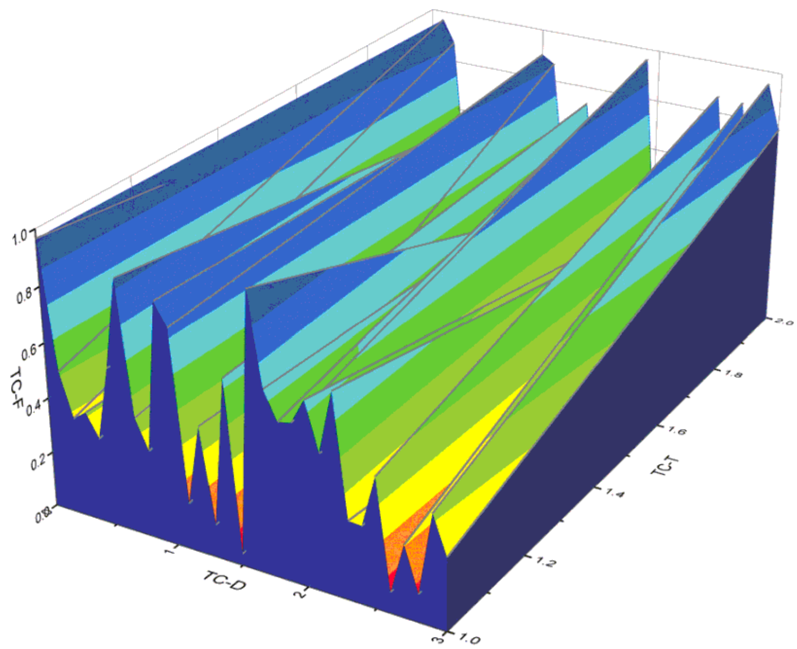

Figure 6. Effect of referral thresholds on total system cost

This study explores the impact of the misdiagnosis rate on the total system cost under different telemedicine service strategies, namely the Gatekeeper service strategy and dual-channel service strategy. The findings suggest that while the total system cost rises with the misdiagnosis rate, the dual-channel service strategy exhibits a non-linear increase. At lower misdiagnosis rates, costs grow more slowly as hospitals scale back telemedicine investments. However, when the misdiagnosis rate exceeds a threshold, costs escalate rapidly, indicating the potential benefit of discontinuing the telemedicine service channel. Additionally, the study discusses the role of big data in healthcare and underscores the evolving landscape of telemedicine service strategies, emphasizing the need for tailored approaches based on practical considerations.

Optimizing Cost Efficiency in Telemedicine Health Analysis Systems with Artificial Intelligence Assistance

In this paper, we examine the impact of waiting time costs for patients in both offline and online units on the overall cost of the healthcare system. Figure 7 illustrates the findings.

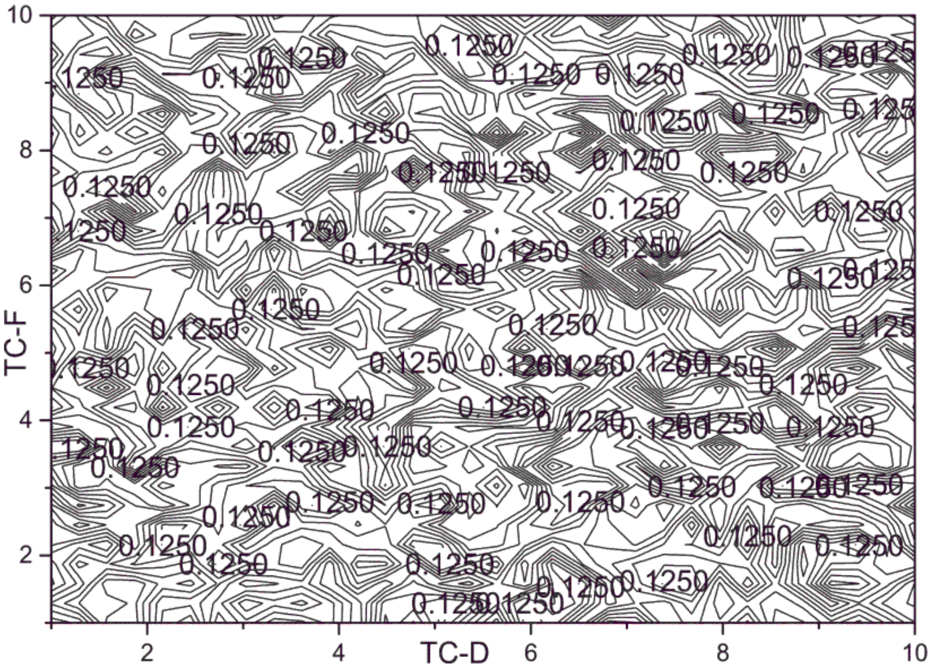

Figure 7. Impact of patient online and offline delays sensitivity on total system cost

The overall system cost rises with an increase in offline unit waiting time costs for various service strategies in public hospitals. Some patients opt for online service channels for telemedicine services, prompting public hospitals to invest more in offline service channels to reduce waiting times. While the total system cost remains unchanged under the offline service strategy as online waiting time costs rise, the Gatekeeper service strategy sees a linear increase in total system cost, and the dual-channel service strategy experiences slow growth. When online waiting time costs reach a certain threshold, the total system cost under the Gatekeeper service strategy surpasses that of the dual-channel and offline service strategies significantly. The gatekeeper service strategy has stringent conditions, and healthcare service system planners should choose carefully based on the actual situation.

Patients can engage in other activities while waiting in the online service channel, making the cost per unit time of waiting online generally lower than waiting offline. Both the gatekeeper service strategy and the dual-channel service strategy have lower total costs than the offline service strategy. For chronic patients, time does not significantly influence patient choice behavior, and both online and offline waiting time costs are lower. However, Figure 7 shows the relative change in the cost of offline or online waiting time, with the dual-channel service strategy being the optimal choice. Most chronic diseases involve long-term, uncomplicated follow-up visits with relatively low patient waiting time sensitivity. Therefore, governments and healthcare organizations can prioritize the implementation of telemedicine dual-channel services for chronic diseases, post-operative recovery and prognosis, and geriatric care.

Optimizing Unit Service Capacity Costs in Artificial Intelligence-Driven Telemedicine Health Analysis Systems

The analysis highlights that as public hospitals invest in enhancing their offline and online service capacities, there are associated costs. The study shows that transitioning from an offline service strategy to a dual-channel service approach becomes optimal when the cost per unit of service capacity for offline services rises or the cost per unit of service capacity for online services falls. The total cost of the gatekeeper service strategy initially differs from and eventually aligns with the total cost under the dual-channel service strategy. Notably, telemedicine services, leveraging lower GP labor costs and efficient resource utilization, tend to have lower medical service costs, particularly in terms of online unit service capacity costs. Lower costs for online service capacity can encourage the adoption of telemedicine services in public hospitals.

This study explores the substitution phenomenon between online and offline service capabilities, wherein they can be interchangeable, but the cost per service capability and misdiagnosis rates may vary. Service capacity substitution is a common occurrence in various service industries, where providers possess multiple service capacities to address diverse market demands. When one service capacity faces a shortage, another can be temporarily utilized to meet customer requirements, similar to the substitution between luxury and regular class seats in airlines or between luxury and regular rooms in hotels. However, in the medical field, there are differences in service quality and functions between online and offline service capabilities, leading to incomplete substitution. This incomplete substitution adds complexity to decision-making in medical institutions, a complexity further compounded when online and offline healthcare services are offered by different providers.

SECTION VI: CONCLUSION

This paper introduces a cloud-converged health Internet of Things (IoT) architecture, emphasizing the integration of health cloud platforms and the sensing layer to enhance user experience and connectivity with people. The proposed architecture comprises the health IoT perception layer, transmission layer, and health cloud service layer, including support and application sub-layers. The architecture is detailed, and a specific cloud-converged health IoT application is presented. The paper also addresses Quality of Service (QoS) for health IoT based on human Local Area Network (LAN) with a multi-level QoS framework, ensuring priority transmission of critical health data. In the realm of emotional perception and interaction in health IoT, the identification of human emotional states using smart device signals is explored. The emotional interaction with robots is achieved through a migration learning algorithm, a continuous conditional random field, and a decision layer artificial intelligence algorithm (Rasool, Ghafoor, & Fareed, 2021). The proposed approach is validated through a sentiment interaction demonstration application. The paper concludes with insights into optimal strategies for public hospitals, government subsidies, and the future direction of research.

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