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# Building a Rehabilitation Walking Behavior Pattern Analysis System in Living Environments

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Population aging is a major hidden concern of society. The biggest impact of population aging on society is the increasing demand for medical care and long-term care, resulting in a heavy burden on social welfare. Therefore, in this study, we designed a wearable device for the rehabilitation of the foot muscles of the elderly, combined with the posture analysis system and integrated with timely data for display on the web. Through IoT, we can not only know the foot muscle strength data, but also know whether the walking posture is standard and whether the user's walking posture is normal. The system can provide medical personnel with data to understand the foot strength health of the user during the process, to achieve the effects of prevention and rehabilitation. The rehabilitation of the elderly usually takes a lot of time. If someone needs to continue supervision, it will take a lot of time and personnel costs. In the long run, the cost of hospital services will increase. Therefore, we integrated wearable devices and IoT technology and present the muscle strength values collected by wearable devices on a web page. Through the analysis results of different methods, the data attribute and prediction prognosis system use the Extreme Gradient Boosting method with high accuracy, thus achieving the goal of cost research. The data analysis system classifies and presents the data on the web page. The nursing staff or medical personnel can view and understand the muscle strength of the rehabilitation personnel who are walking through the data analysis system on the web page.

## 1. Introduction

The ratio of the elderly population to the total population in the world from 1960 to 2060 is shown in Fig. 1. From the figure, the proportion of the elderly population in China is still relatively low, but the rate of increase is high. It can be clearly seen that the number of elderly people over 65 is gradually increasing. Since transitioning to an aged society in 2018, Taiwan's

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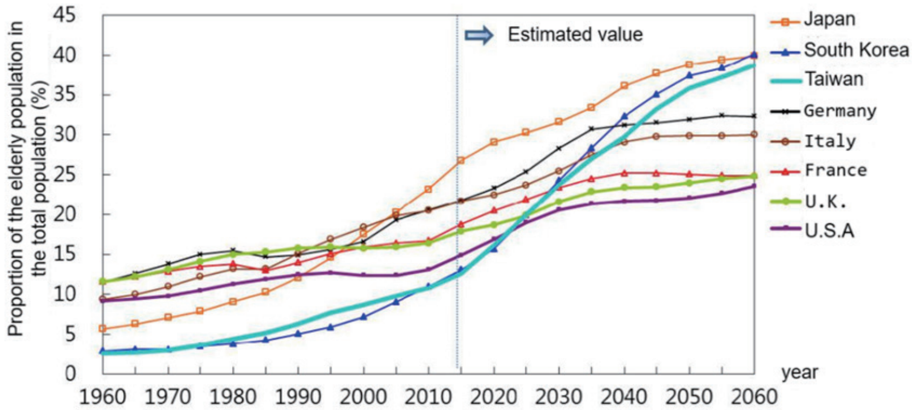


Fig. 1. (Color online) Ratio of elderly population to total population in the world.(1)

demographic structure has been changing. In 2020, the population aged 65 and above exceeded 15%, and by 2025, the elderly population will account for 20.1% of the total population, meaning that one in every five people will be elderly.(2) From 2052, the share will be higher than that of major countries, only slightly lower than that of South Korea, and will start to exceed 40% in 2057.

With the aging trend, wearable devices are becoming increasingly advanced, and they also break through the limitations of rehabilitation space and equipment. Since 2014, many research institutions have carried out research on assistive devices for patients with native tremor. Now, they have successfully developed highly sensitive tactile wearable assistive devices to provide a stable hand shock suppression effect and significantly improve the control of hand movements of silver-haired and native tremor patients.(3)

In this study, a self-built network server was used for monitoring. We collected the muscle strength and triaxial acceleration values of people who wore sensor equipment during rehabilitation walking. At the same time, the data were uploaded to a research server for model training. The training model in this study can analyze the current walking posture of people in rehabilitation through the analysis of muscle force sensing and triaxial acceleration data. Doctors and medical personnel can then know whether the elderly who are currently undergoing rehabilitation have completed the standard actions ordered by doctors and medical personnel during the rehabilitation process.

Faisal *et al.*(4) explained that the movement ability is one of the important factors for people to maintain gait and good function of lower joints. Gait is monitored through wearable multi-sensors. Borghetti *et al.* mainly analyzed the angle of knee joint.(5) The purpose of this study is to develop a multi-sensor to measure thigh motion during walking and monitor thigh tilt angle, flexion, and extension.

Zhou *et al.*(6) discussed the effect of gait analysis on the user's motion state and used a nine-axis posture sensor to develop an intelligent walking stick. The number of steps, step length, and step speed were calculated. Brzostowski(7) solved the problem that when tracking and measuring human motion, the signal will be affected by the surrounding noise and will lead to accuracy. He proposed a method to reduce the effects of noise and cause erroneous signals. Razavi *et al.*(8)

studied and proposed an algorithm that can detect the stationary phase by taking the buffered accelerometer and gyroscope data as input. During this period, pseudo-measurements such as zero speed or heading stability update were applied. In recent years, big data analysis has become an emerging method for analyzing data and extracting information and its relationships in a wide range of application fields. It is mainly used to analyze and identify different patterns, relationships, and trends in a large amount of data. Big data can lead to detecting and preventing problems before they occur.(9)

In our study, compared with other research studies, we focused on the rehabilitation of foot muscle strength in the elderly while also using wearable devices to monitor gait. We combined a posture analysis system and displayed real-time data on a web page, providing more comprehensive foot muscle strength data and gait monitoring. Additionally, we used the LoRA indoor positioning system to help calculate walking laps and employed the Extreme Gradient Boosting (XGBoost) model to predict gait during the multi-model analysis process. By adding new features or increasing the amount of sample data, we improved accuracy, which can also reduce signal errors to some extent. This provides more detailed gait data, aiding medical personnel in diagnosis and rehabilitation guidance. Compared with other studies, our research offers a certain level of innovation and practicality in real-time monitoring and data application, especially in the accuracy of gait prediction using the XGBoost model. Therefore, we recommend applying this device and technical approach in the rehabilitation and gait monitoring of foot muscle strength in the elderly to improve prediction accuracy and rehabilitation effectiveness.

The development of electronic medical records has evolved from the electronic health information system used to transcribe paper records and record patient personal information, physiological data, and disease health information in the early stage. The development track of medical big data has changed from paper records in the past, the digitization of paper-based information, and the storage of medical records to today's multi-information integration. The speed of medical big data collection is incredible. Health monitoring data is generated once every second. Medical big data is mainly used as clinical data for the monitoring and warning of chronic diseases and the detection and collection of daily activities and physical characteristics.(10) The classification algorithm can adopt logical regression, classification tree, support vector machine, random forest, and artificial neural network. Regression algorithms can predict the value of entity attributes and include linear regression, decision tree, naive Bayesian classification, fuzzy classification, and artificial neural network or other algorithms. Machine learning is a practical resource for healthcare providers.(11,12)

XGBoost is a kind of Gradient Boosted Tree (GBDT), which keeps the original model unchanged each time, and adds a new function to the model to correct the error of the previous tree to improve the overall model. It is mainly used to solve supervised learning, which can be used for classification and regression problems.(13–14) Random search specifies the range of parameters, and sample parameters with uniform distribution train with the parameters(15) and use cross validation to ensure the generalization of the model.(16) The approach of this study was to take multiple random searches to find the near peaks of multiple better parameters, and then turn these near peaks into small ranges for more detailed grid searches to find the peaks of each near peak, and then select the best parameters according to the final evaluation results.(17)

## 2. System Model

In this study, we aimed to develop a wearable device for the rehabilitation of foot muscle strength in the elderly, integrating IoT technology to achieve real-time data monitoring and display. Compared with other studies that also use wearable devices to monitor gait, our research focused on the rehabilitation of foot muscle strength in the elderly. It combined a posture analysis system and displayed real-time data on a web page, providing more comprehensive data on foot muscle strength and gait monitoring.

First, we utilized the LoRA indoor positioning system to help calculate the number of walking laps, which is part of IoT technology. LoRA technology, with its low power consumption and long-distance transmission capabilities, is suitable for use in wearable devices. Through LoRA, we can accurately locate and track the walking path of users in indoor environments, which is crucial for accurately calculating the number of walking laps.

Second, in the multi-model analysis process, we employed the XGBoost model to predict gait. The data are transmitted in real time to the cloud through IoT technology for processing and analysis. The XGBoost model can make high-precision predictions based on the collected data, improving accuracy by adding new features or increasing the amount of sample data, thus reducing signal errors. The application of these real-time data provides detailed gait information, assisting medical personnel in diagnosis and rehabilitation guidance. Furthermore, the application of IoT technology enables real-time data to be conveniently displayed on a web page, offering a user-friendly data viewing platform for both medical personnel and users. Through the web interface, medical personnel can monitor the walking status and foot muscle strength data of the elderly in real time, promptly adjusting rehabilitation plans to enhance the effectiveness of rehabilitation. Users can also access their foot muscle strength status via the web and make self-adjustments based on the feedback data. Through the application of IoT technology, our research demonstrates great potential in improving the rehabilitation outcomes of foot muscle strength in the elderly.

The system architecture of this study, which can be divided into three parts, namely, sensor hardware equipment, a wireless network communication network, and a data analysis system, is shown in Fig. 2. The sensor hardware device was developed by this research institute and can be configured on the lower leg of the human body for real-time sensing data transmission. Wireless

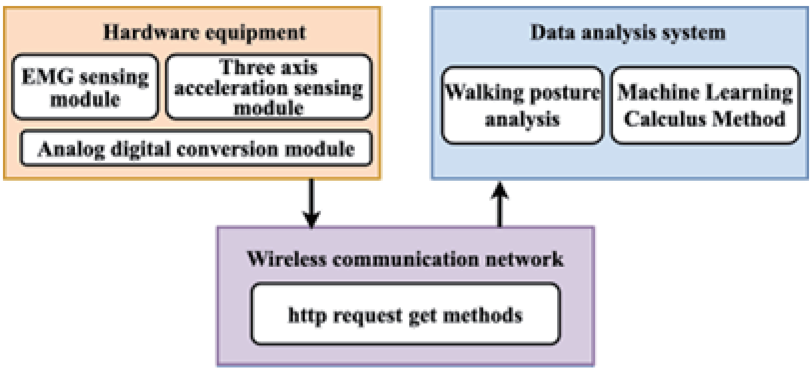


Fig. 2. (Color online) System architecture.

network communication mainly receives sensor values and transmits the collected data to the server in a stable and efficient manner. The data analysis system was built on the server background and analyzes the data of walking posture. In this study, we also added machine learning technology to analyze the posture of the data collected by the sensor to predict whether the walking habits, posture, and foot muscle strength of the rehabilitation personnel are in good condition.

Communication hardware equipment includes a muscle force sensing module, a three-axis sensing module, and an analog-to-digital converter (ADC) chip module, which are mainly used to transmit data. The muscle force sensing, three-axis sensing, and communication modules are combined to form a device for the real-time collection of walking data in this study.

Wireless network communication includes the communication between all communication devices and the mode of data transmission, and the data is sent to the server through the IoT for calculation. Among them, the communication equipment of each node can determine the direction of the data source and data transmission, so if a node has a certain condition or failure, one can immediately determine where the node has an error. In addition, to secure data transmission, we use the HTTP protocol as the data transmission protocol between devices.

This system used the machine learning algorithm for attitude analysis in the data analysis system. The data collected during rehabilitation walking were input into machine learning for model training. Machine learning can judge whether the current rehabilitation walking posture is standard through the data feature field. The machine learning model can predict the collected data in the rehabilitation process of the rehabilitation personnel and predict whether the walking habits, posture, and foot muscle strength data of the rehabilitation personnel are in good condition, which can be referred to by doctors and medical personnel.

In this research, we independently developed and implemented a low-power communication device that can transmit data far away for rehabilitation needs[18] and can be installed in the wearable assistive devices used by the elderly in rehabilitation. Considering applicability and practicability, the equipment not affected by the terrain and environment will be considered in the signal transmission module. In addition, the module also needs to consider the transmission strength and stability of the wireless signal to avoid problems during the system operation.

Figure 3 shows the MyoWare Muscle Sensor muscle inductance sensor module (model no. SEN-13723) used in this study. MyoWare is a muscle sensor chip that can sense the potential difference on the muscle through an electrode patch, judge the muscle force of the electrode patch position, and then send an electronic signal to the device.

Figure 4 shows the 16-bit ADC chip module (model no. ADS1115) used in this study. Its main purpose is to convert the output signal of the sensor into a digital signal before subsequent data transmission. The output signals of the high-precision analog triaxial acceleration and EMG

Fig. 3. (Color online) MyoWare Muscle Sensor module.

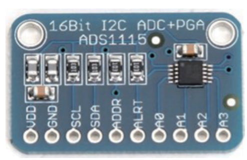


Fig. 4. (Color online) 16-bit analog-to-digital conversion chip module.

sensor modules used in this study are analog signals. Therefore, it is necessary to use a 16-bit ADC chip module to convert the signals.

Figure 5 shows the high-precision analog triaxial acceleration sensor (model no. GY-61-ADXL335) used in this study. This sensor is a small, thin, and low-power triaxial accelerometer, which provides the voltage output after signal conditioning, and can measure acceleration in the minimum ±3 g full range. It can measure the static gravity acceleration in tilt detection applications and the dynamic acceleration caused by motion, impact, or vibration.(19)

Figure 6 shows the Raspberry Pi Zero entity diagram used in this study. Raspberry Pi Zero can relate to various sensors and many electronic components, such as infrared, ultrasonic, thermistor, and photosensitive resistors, and servo motors. It can use Python, a highly developed programming language, for various hardware controls. It also has Wi-Fi and Bluetooth functions. Wi-Fi and Bluetooth can be used without purchasing additional Wi-Fi and Bluetooth modules for expansion and can also be controlled through Python.

Figure 7 shows the hardware and actual wearing of the wearable device. The wearable device designed in this study is worn on the right leg and uses the patch of the muscle inductance sensor to stick it on the calf muscle. After the power supply starts Raspberry Pi Zero, one can control the Raspberry Pi Zero through the remote end. After inputting the user's basic information, one can run the Python program to start the data collection of walking posture.

The wearable device designed in this study is worn at the upper part of the right leg, and the triaxial accelerometer is placed as shown in Fig. 7. The $x$-axis is the acceleration data perpendicular to the ground, the $y$-axis is the front and rear acceleration data horizontal to the ground, and the $z$-axis is the left and right acceleration data horizontal to the ground. In this study, the wearable device is glued to the lower leg strap by using devil's felt, which has strong adhesion and is easy to disassemble, and it is not necessary to bind the wearing strap tightly to the lower leg of the user, which can avoid causing discomfort to the lower leg of the user.

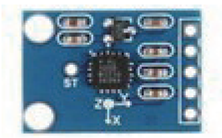

Fig. 5. (Color online) High-precision analog triaxial acceleration sensor module.

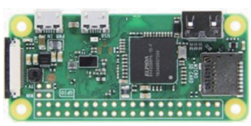

Fig. 6. (Color online) Raspberry Pi Zero entity diagram.

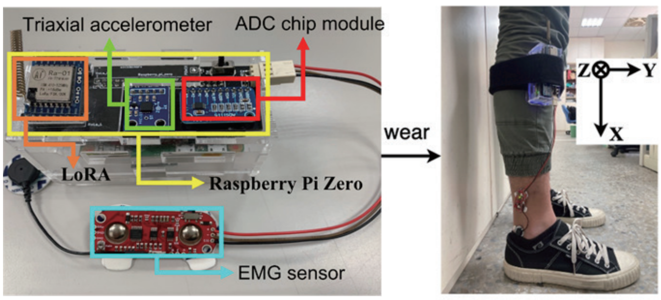


Fig. 7. (Color online) Wearable device hardware and actual wear diagram.

## 3. Implementation Method

The system monitors the walking posture of the elderly in rehabilitation through simple hardware equipment and transmits the posture data collected during the monitoring to the back-end server for analysis and calculation. The monitoring data include muscle strength and triaxial acceleration data. The purpose of this system is to analyze the rehabilitation walking status of the elderly and confirm whether the elderly have performed rehabilitation according to the walking posture prescribed by the doctor, so that the medical staff and relevant personnel can understand the rehabilitation situation of the rehabilitation party.

This research system can upload the rehabilitation activity information of the elderly to the website server and design the web page display screen. The data line chart is provided for doctors and medical personnel to use the two functions proposed later: (1) inform the elderly of abnormal activities in a timely manner and (2) record activity information and analyze actions for a long time.

Figure 8 shows the system development tools and technical schematic diagram. The server was built on the basis of the Windows operating system, which has a high market penetration rate. The Windows system operation interface is also relatively easy for medical personnel to use. The web server was written using Python, which is a cross-platform programming language. Under the current boom of the artificial intelligence industry, this programming language has relatively many resources on the Internet and is easier to develop than other programming languages. The website server was set up using Flask. Flask is a lightweight web application framework based on Python. Therefore, Flask was selected as the website framework for this study.

Figure 9 shows the data of normal walking collected in this study. The data on the left side of the normal walking data graph is the value of the triaxial accelerometer. The vibration amplitude of *x*, *y*, and *z* data is relatively intense and frequent, and the data variation range is about 2–−2. The data on the right is the value of the EMG sensor, and its variation range is about 0–1.5.

Figure 10 shows the data graph of walking with legs in this study. The data on the left is the value of the triaxial accelerometer. The vibration amplitude of *x*, *y*, and *z* data is relatively gentle, and the data variation range is about 1–−1. The data on the right is the value of the EMG sensor, and its variation range is about 0–0.6.

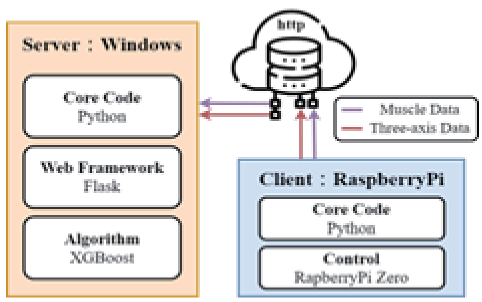


Fig. 8. (Color online) System development tools and technical schematic diagram.

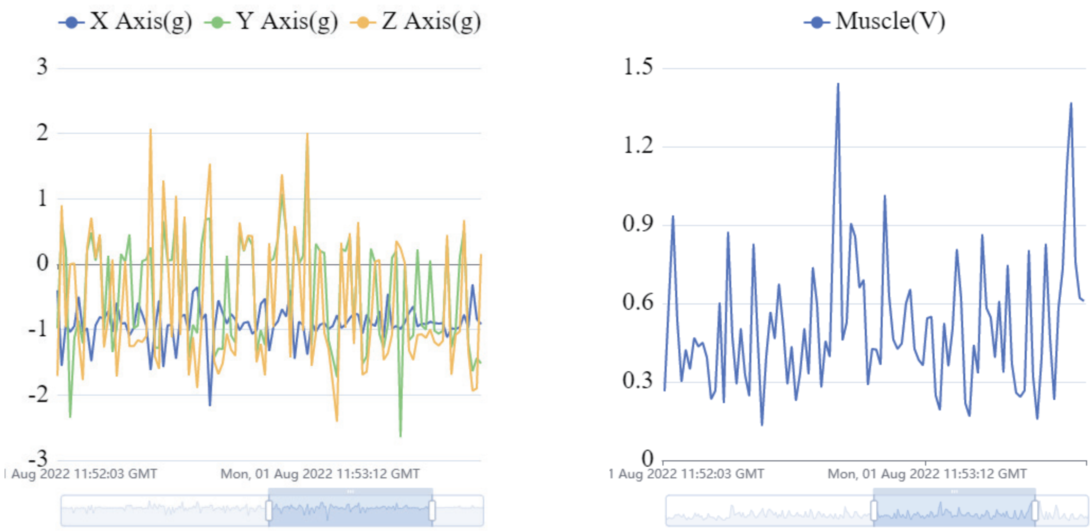


Fig. 9. (Color online) Data chart of normal walking.


Fig. 10. (Color online) Data chart of walking with legs.

Figure 11 shows the data of leg walking collected in this study. The data on the left side of Fig. 11 show the values of the triaxial accelerometer. The vibration amplitude of $x$, $y$, and $z$ data is also relatively intense, but the data density is relatively lower than that in the case of normal walking. The data variation range is about 0.5–−2. The data on the right side of Fig. 11 is the value of the EMG sensor, and its variation range is about 0–2.5.

Figure 12 shows the algorithm model for attitude analysis using various classification models in this study. The sample ratio of the data set totals 4825 data, and it is known that the data can be classified, but they must be labeled through subsequent data processing. The data set was


Fig. 11. (Color online) Data chart of walking with legs raised.

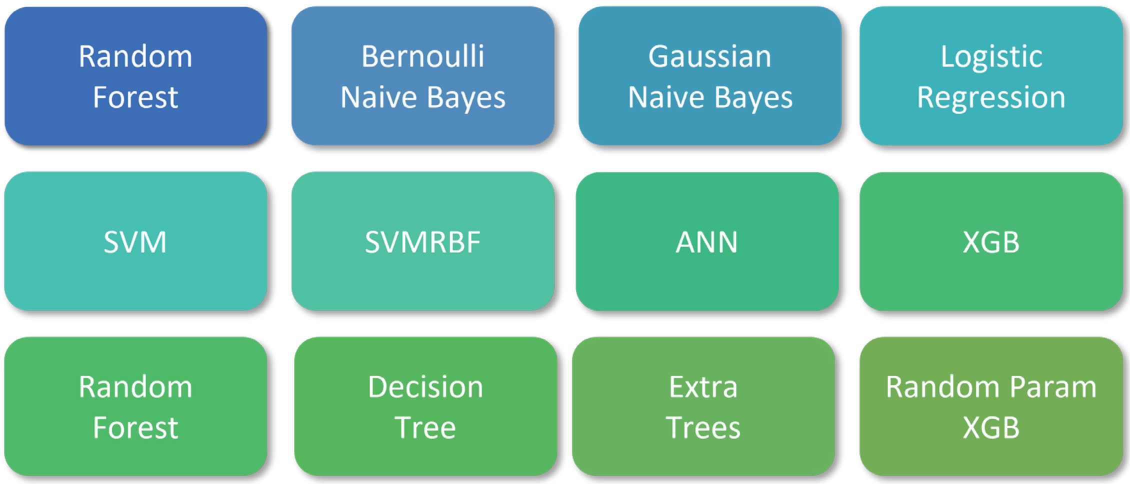


Fig. 12. (Color online) Types of prediction model using tests.

labeled with three different posture analyses, namely, normal walking (model classification should be class 0), dragging walking (model classification should be class 1), and lifting walking (model prediction classification should be class 2).

## 4. Results and Analysis

As for the algorithm used in this study, as shown in Fig. 12, the classification algorithm of supervised learning can be used to predict from the data set structure. In the test phase, various classification models were selected to find the prediction model suitable for this study.

In this study, we used five data processing methods, which were divided into Z-Core standardization (preprocessing), raw data (no preprocessing), pre- and post-data comparison (VectorData), low-pass filtering (FilterData), and frame data (FrameData) in this order. A total of five methods were used as training data for classification algorithm model training.

We preprocessed the data of $x$, $y$, $z$, muscle sensor values (*muscle*), but compared $x$, $y$, $z$, *muscle*, $X_{n+1} - X_n$, $Y_{n+1} - Y_n$, $Z_{n+1} - Z_n$. We compared the differences between the next frame and the previous frame. Then, we filtered the music, removed the fields with values higher than 4, and finally used the $x$, $y$, $z$, music data $\{(X_n, X_{n+1}, X_{n+2}, X_{n+3}, X_{n+4}), (Y_n, Y_{n+1}, Y_{n+2}, Y_{n+3}, Y_{n+4})$, and $(Z_n, Z_{n+1}, Z_{n+2}, Z_{n+3}, Z_{n+4})\}$ as the training data input in frame mode.

Figure 13 shows the prediction results of various classification models. From the result graph, we can see that the accuracy of the XGBoost algorithm is relatively higher than those of the other algorithm models. The prediction accuracies of XGBoost, which is the final model for attitude analysis in this study, are 81.06 and 81.62%. The goal of this system is to analyze the walking condition of the elderly and confirm whether the elderly walk according to the prescribed number of laps so that the medical staff and relevant personnel can understand the situation of the person concerned.

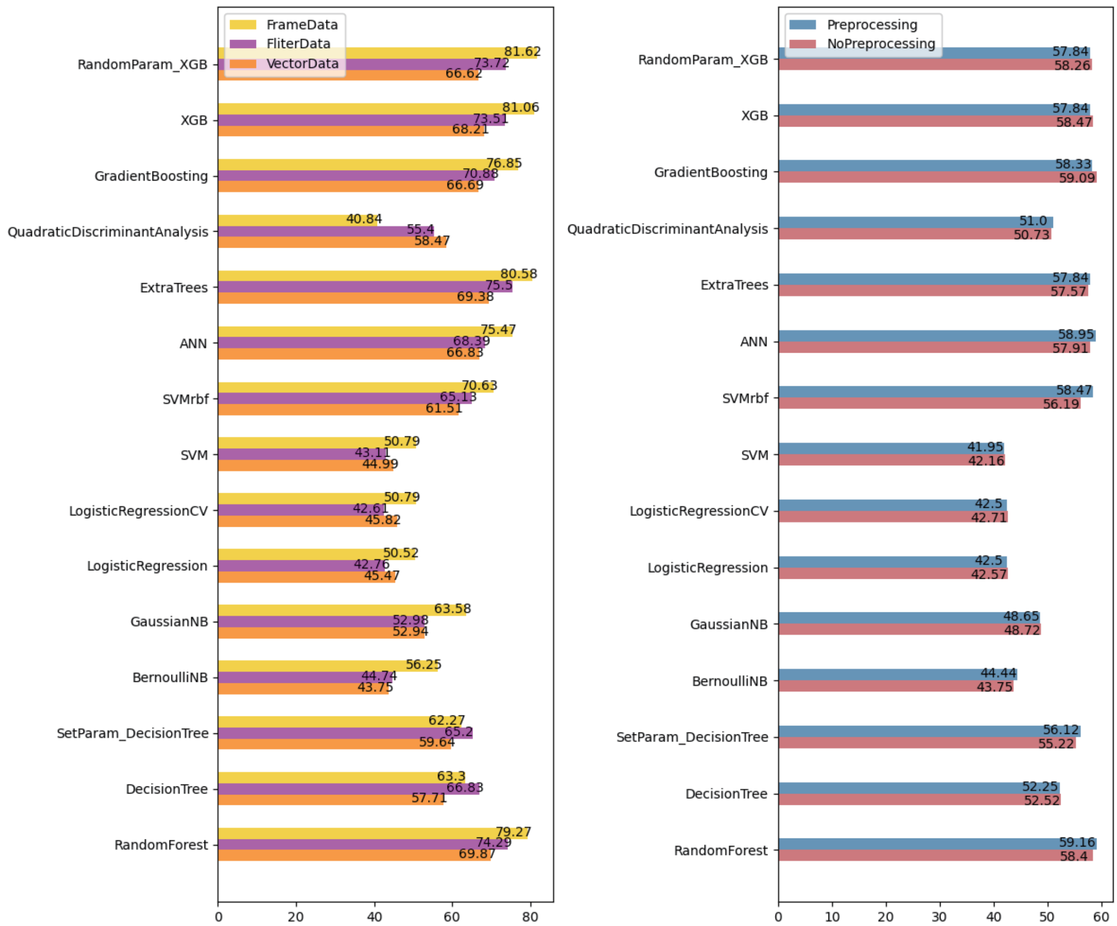


Fig. 13. (Color online) Prediction results of multiple classification models.

LoRA[20,21] has been a popular technology in recent years, and most of it is applied to IoT. LoRA has a transmission range of 15 to 20 km and can transmit the rehabilitation monitoring data over a long distance. The rehabilitation site will not be limited to the hospital site, and its low power consumption features extend the service life of the battery. LoRA can be used for indoor positioning through the positioning technology of receiving signal strength indication (RSSI).[22,23] Therefore, LoRA was combined with wearable devices to monitor whether the elderly have completed the number of walking laps specified by the doctor during rehabilitation.

Figure 14 shows the hardware diagram of LoRA module A, B, and C devices for indoor positioning. The LoRA module A, B, and C devices will be placed in the indoor triangle position. When the wearable device is connected to the power supply, the LoRA module receiver of the wearable device will receive the signals of the three transmitters. When the three transmitters have normal operation to transmit signals to the receiver, the receiver will start counting whether there is a position passing through the transmitters A, B, and C. If there is a position passing through the transmitter, the receiver will record, and when the transmitters A, B, and C have records, the number of laps will be increased by one. This action is repeated until the recovery is completed. The number of laps will be uploaded to the database through the network.

The LoRA module receiver on the device will first transmit data with the three LoRA module transmitters A, B, and C arranged in the room to confirm whether they have received the data. When the receiver and the three transmitters A, B, and C receive the data, the LoRA module's function is to use RSSI technology to track the elderly walking in rehabilitation and confirm the number of laps. The rehabilitation personnel will record when passing near the transmitters A, B, and C.

Figure 15 is the schematic diagram of the rehabilitation monitoring and server online update database. When walking in rehabilitation, the muscle strength device on the foot is connected to the server through Wi-Fi, and the collected data are stored in the database through the server. The data analysis system will classify the data in the database and present them on the web page, so that nursing staff or medical personnel can view and understand the muscle strength of the

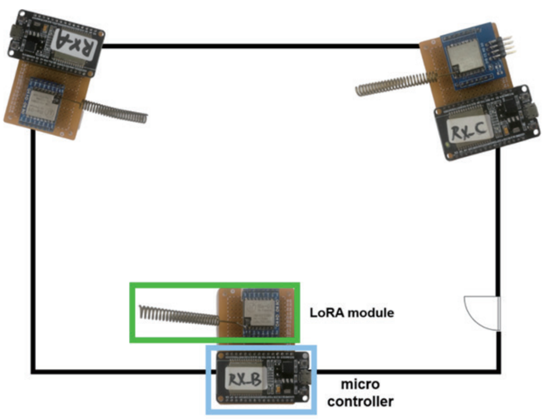


Fig. 14. (Color online) Hardware diagram of LoRA module A, B, and C devices for indoor positioning.

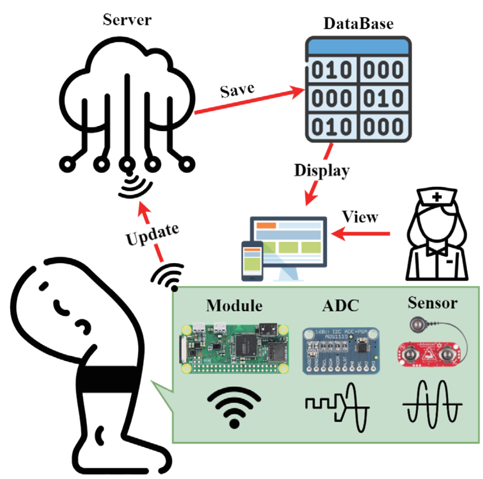


Fig. 15. (Color online) Rehabilitation monitoring and server online update database.

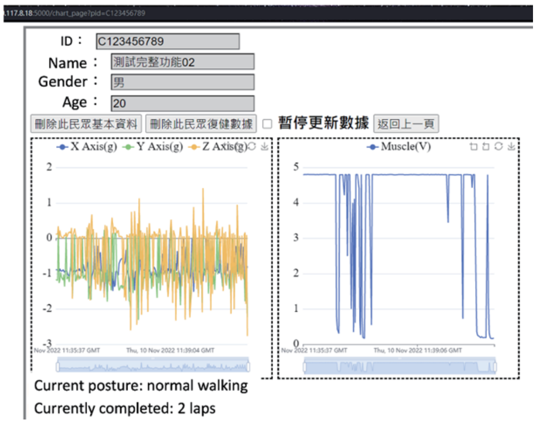


Fig. 16. (Color online) Restoration monitoring screen of normal walking.

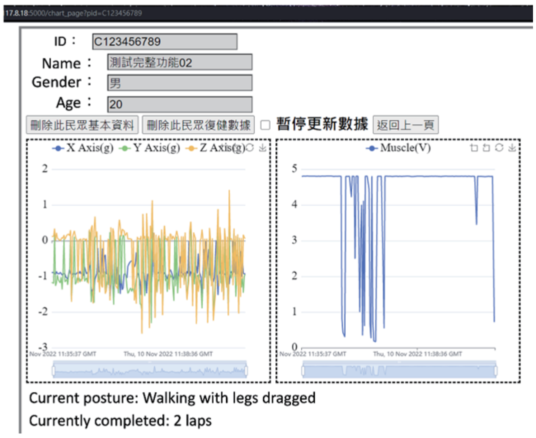


Fig. 17. (Color online) Rehabilitation monitoring screen of dragging feet.

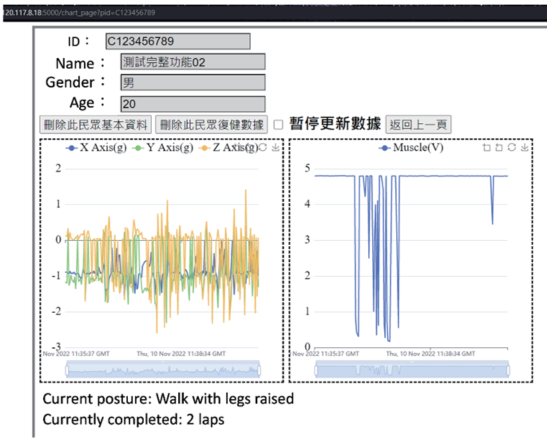


Fig. 18. (Color online) Rehabilitation monitoring screen of walking with legs raised.

rehabilitation personnel who are walking through the data analysis system in the web page, as shown in Figs. 16–18.

MySQL was selected as the database type for data storage in this study. MySQL can be concatenated through Python. There are stricter rules for data storage than for other databases. It can back up data by exporting the database.

## 5. Conclusions

In this study, we designed a system that can make the elderly, who are recovering or want to prevent health care, aware of their current foot muscle strength and be alert to themselves. However, the global spread of the COVID-19 pandemic in recent years has made many people stay indoors for a long time. We hope that some elderly who do not like outdoor activities or who often stay at home can begin to be interested in outdoor activities and sports through this system. The system is used by people who are slightly older or the elderly, and its functions can be put into the series of long-term care. After all, many elderly people in the aging society will have some symptoms of decline; in particular, foot degradation is the fastest. Therefore, this study is of great help in this respect. In addition, this can be achieved for people who are slightly older and have the concept of aging prevention.

In this study, we can measure the current instant foot muscle strength status during walking and we can also calculate the number of walking laps through LoRA indoor positioning. During walking, the system found through multi-model analysis that the XGBoost model can predict the walking posture including normal walking, leg lifting walking, and leg dragging walking, with the analysis accuracies of 81.06 and 81.62%. Thus, we suggest that the XGBoost model can be used to predict the walking posture in this situation. If the characteristic value or walking posture data is added to the sample without affecting the service object, the accuracy can be further improved.

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