Investigating the Development of an AI-Based Classification System for Detecting Sarcopenia in the Elderly through Gait and Posture Analysis

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Abstract. Taiwan is currently undergoing an irreversible social transformation due to its aging population. According to recent statistics from the Ministry of Health and Welfare, there has been a rapid increase in the elderly demographic, particularly those over 65 years of age. This demographic shift poses critical challenges for public health and healthcare services, particularly in managing fall risks among the elderly. These risks significantly impact healthcare systems and affect the quality of life and autonomy of the elderly population. With the rapid progression of medical technology and information science, the application of artificial intelligence (AI) and deep learning in geriatric medicine is gaining prominence. These technologies are increasingly recognized for their effectiveness in analyzing the posture and gait of elderly people and identifying high-risk factors for falls. This research aims to integrate medical expertise with information technology by employing AI to assess the severity of sarcopenia and predict the risks of falls, thus improving health protection for the elderly. As age progresses, sarcopenia becomes prevalent among the elderly, characterized by decreased muscle mass and functional decline.

Keywords: Artificial Intelligence, Elderly, Sarcopenia, Human Gait and Posture.

1 Introduction

As our country is undergoing the process of demographic aging, the number of people over the age of 65 is rapidly increasing. According to statistics from the Ministry of Health and Welfare, falls have become one of the most common accidental injuries among the elderly. However, there is limited research in this area. Therefore, this research aims to integrate the fields of medicine and information technology by using artificial intelligence to analyze gait and posture to help classify the severity of sarcopenia.

This research project aims to create an innovative methodology that combines medical knowledge with information technology to use AI to analyze gait and posture. This analysis can help classify the severity of sarcopenia and predict the risk of falls. This research aims to provide an accurate and convenient assessment tool for elderly healthcare, filling a current gap in the field; furthermore, the anticipated impact of this research is significant. On the one hand, it will reduce the use of medical and care resources and improve the efficiency of medical care. On the other hand, immediate monitoring and early intervention are expected to significantly reduce the incidence of falls among the elderly, thereby improving their quality of life.

2 The effects of muscle aging on the elderly

This phenomenon involves a complex biomedical process in which multiple physiological, molecular, and environmental factors play a role. This research aims to provide an in-depth discussion of the various factors that influence skeletal muscle aging, including genetics, lifestyle, nutrition, chronic diseases, neuromuscular interactions, hormonal changes, etc. With further discussion of how these factors interact to cause a decline in muscle mass and function.

Genetic factors play a significant role in the process of muscle aging. With the findings of these genetic factors, it is possible to explain why there are significant differences in muscle aging between individuals [1]. Hormonal changes have a significant impact on muscle aging. Aging causes changes in hormone levels that significantly affect muscle mass and function. This can result in a loss of muscle mass and decreased muscle strength. These changes highlight the important role of hormones in maintaining muscle health [2]. Regular exercise stimulates muscle growth, enhancing muscle strength and endurance while decelerating the process of muscle atrophy. Therefore, it is crucial to lead an active lifestyle to prevent muscle aging [3].

Adequate protein intake is essential to maintain muscle mass and function, particularly in older individuals. It benefits muscle function by providing enough vitamin D, calcium, and other micronutrients. These nutrients help maintain muscle mass and promote overall health [4]. Chronic inflammation and metabolic abnormalities often accompany these disorders, which can be detrimental to muscle tissue, resulting in a loss of muscle mass and function [5]. Aging may lead to deterioration of neuromuscular junctions, resulting in less effective muscle stimulation. Neurodegenerative processes impact muscle contraction coordination and strength, ultimately affecting overall muscle function. Understanding this process is crucial for developing targeted therapeutic strategies [6].

3 Methodology

3.1 Research data collection and analysis

Human motion recognition is a crucial research area in computer vision, with widespread applications in fields such as intelligent surveillance, customer analysis, and behavior analysis of purchases. However, accurately recognizing human movements remains a great challenge due to the scene's complexity, occlusion, and variations in viewing angles. Most of the current methods first extract hand-designed characteristics from the raw video and then train the classifier based on these characteristics [7]. Each convolutional layer comprises multiple feature maps generated by convolving the feature maps of the previous layer with activation functions. The pooling layer is downsampled on the feature maps to increase the insensitivity of the model to small input deformations. The final classification is performed using the fully connected layer [8].

The convolution kernel performs sliding window operations on the input data's spatial dimensions (length, width, and depth) to perform the interpolation operation, retrieving a value from the output data. In the convolutional layer, each feature map is connected to several neighboring consecutive frames in the previous layer to capture motion information [9].

3.2 Artificial intelligence algorithms for physiological measurement data

We chose the random forest algorithm as our main instrument to model the prediction of the characteristics of patients with sarcopenia. We use random forests to analyze the data on which we build a predictive model. It combines multiple decision tree models to improve prediction performance and reduce the risk of overfitting. The random forest is constructing a forest through the random distribution of training data, and each decision tree is trained on a different subset of the data [10].

Human gait information refers to the characteristics of a person's feet during daily walking. Typically, gait characteristics such as onset, length, height and stride, uniformity, continuity, walking distance, and deviation are included. Human gait can be assessed by analyzing these data, identifying abnormalities, determining influencing factors, and evaluating falls [11].

The intelligent gait analysis system captures human gait characteristics through electronic pressure plates and converts them into data signals (as shown in Fig. 1). These data signals are processed by a data analysis device to reflect the characteristics of the human gait pattern. For the implementation of intelligent gait assessment [12], a human gait assessment system and method will be established in this research. It can monitor human gait information and analyze it and provide results that can be used to assess gait in patients with sarcopenia.

Fig. 1. Plantar pressure measurement devices (PMDs).

The device automatically records the pressure distribution on the soles of the feet, including the intensity and distribution of pressure in different areas of the soles. Continuous data collection provides a complete picture of plantar pressure distribution, which contains information on the pressure of each part of the sole of the foot (as shown in Fig. 2).

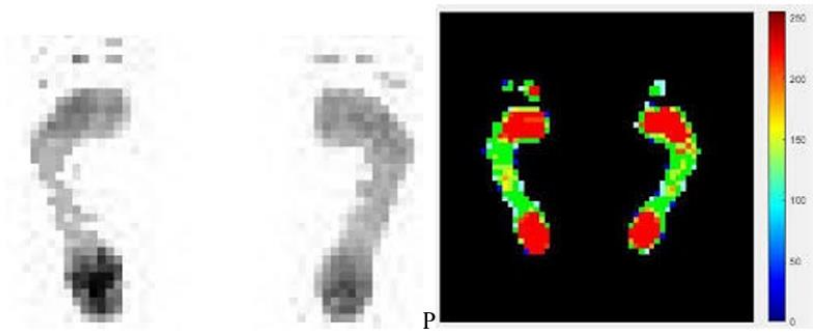

Fig. 2. Plantar pressure images.

In this research, the GBDT will be used to analyze plantar pressure images for gait classification and assessment. The GBDT algorithm is an important method that belongs to the boosting algorithms in integrated learning [13].

4 The application of artificial intelligence in gait analysis systems

In modern medicine and sports science, gait analysis systems are indispensable. Provides a wealth of information on human gait, which is of great value for many research and clinical applications [14]. These sensors detect movement and strength information related to walking and convert it into digital signals. Analysis software is utilized to process and analyze the data, extracting parameters and characteristics related to the gait [15].

Gait analysis systems can provide valuable information and indicators with various applications in different fields. By analyzing the gait cycle diagram, power curve and speed curve, these parameters can be obtained [16]. These data and indicators have

significant implications for researchers and clinicians. To assess the efficacy of the treatment and modify the rehabilitation program [17]. In the field of sports science, gait analysis systems are also widely used to investigate and optimize sports performance. By analyzing gait data, researchers can explore the effects of different sports techniques and training regimens on gait to help optimize training and improve athletic performance [18].

All of these sensors can be placed on different parts of the body or under the floor. These data can be used to identify asymmetries or compare them with normal parameters to understand gait characteristics better [19].

5 Conclusion

Utilization of multifunctional body fat measuring instruments and instruments to measure grip strength for the simultaneous collection of data on multiple biometric characteristics. Measurements included body weight, body fat percentage, body water percentage, visceral fat, muscle quantity, muscle mass, estimated bone mass, basal metabolic rate, physiological age, height, BMI and MBA, and grip strength. Integrate the random forest algorithm to build a multilevel analysis and an AI model of the characteristics of patients with sarcopenia. The following instruments will be used to collect physiological parameters to provide a more accurate prediction of sarcopenia and personalized treatment recommendations.

The solution for constructing the IOT case management system for sarcopenia integration will utilize PHP in combination with Microsoft SQL and Responsive Web Design (RWD) technologies. The technical architecture was selected to guarantee the system's stability, scalability, and security. Microsoft SQL will be utilized to construct and administer a centralized database to store the physiological data collected. At the same time, we will use PHP to develop front-end and back-end applications that allow users and healthcare professionals to access and analyze data. Additionally, implementing the RWD technique will ensure optimal functionality across various devices and screen sizes.

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