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TIME SERIES DATA ANALYSIS AND MODELING OF MACHINE LEARNING METHODS IN LIMB FUNCTION ASSESSMENT

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Abstract. In response to the current needs of patients with limb dysfunction, with the goal of safety, real-time, non-invasive, and intelligent rehabilitation assessment, and with limb dysfunction patients as the research object, the author uses intelligent perception technology to obtain rehabilitation data of patients, fully utilizing the advantages of the data itself, and is committed to achieving rehabilitation training and muscle fatigue assessment for limb dysfunction patients. The author developed an assessment model for limb function evaluation using the Dynamic Time Warping K-Nearest Neighbor (DTW-KNN) algorithm and a Long Short-Term Memory (LSTM) neural network-based evaluation model. Based on the experimental findings, it was demonstrated that DTW-KNN effectively categorizes and assesses the rehabilitation motions of upper limbs during elbow flexion under various completion scenarios. Patients have the flexibility to conduct independent and effective upper limb rehabilitation training at home using the upper limb functional rehabilitation system, without any constraints of time or space. By enabling physicians to promptly modify the rehabilitation plan, the system significantly addresses the limitations of conventional upper limb rehabilitation approaches, lowers the medical expenses associated with stroke upper limb rehabilitation, and helps mitigate the shortage of rehabilitation specialists. Utilizing the developed upper limb functional rehabilitation system, the author gathered a set of inertial sensing data on upper limb rehabilitation movements, showcasing prominent temporal features. Consequently, to address this issue, the author proposes the use of Long Short-Term Memory (LSTM) neural network - a recurrent neural network (RNN) with superior temporal data processing capabilities. Based on the multi-dimensional inertial sensing data collected by the upper limb rehabilitation system, the author constructs a recurrent neural network classification model. The model can accurately classify and evaluate different types of upper limb rehabilitation movements under varying completion scenarios. The experimental results indicate that: The overall classification accuracy of DTW-KNN for elbow flexion, elbow flexion&forearm abduction, and shoulder flexion in upper limb rehabilitation movements is 71.8%, 47.9%, and 68.8%, respectively. It was observed that the classification accuracies of LSTM neural network model were 98.2%, 93.3%, and 95.1%, respectively. This marks a notable improvement in the classification accuracy of LSTM neural network model compared to DTW-KNN, with an increase of 26.4%, 45.4%, and 26.3%, respectively. LSTM has a significant advantage over DTW-KNN in terms of classification time, with less classification time.

Key words: Limb rehabilitation, Machine learning, Sensing data, Timing, neural network

1. Introduction. Limb dysfunction refers to clinical pathological changes in the limbs that are not controlled by thinking. Effective rehabilitation training and muscle fatigue monitoring are the basic treatment plans for patients with limb dysfunction, aimed at avoiding disuse atrophy of the patient's limb muscles and improving the body's immunity. At present, medical resources are limited, rehabilitation costs are high, and there are a large number of patients with limb dysfunction. Traditional rehabilitation training models have low efficiency and lack a comprehensive evaluation system for limb rehabilitation training [1]. With the emergence of intelligent rehabilitation, the key to tracking and managing patient rehabilitation is to efficiently and accurately identify and obtain patient rehabilitation training actions, and to conduct real-time muscle fatigue assessment of patient rehabilitation to ensure the safety of rehabilitation training.

At present, there is a huge gap between the medical and health service system and the health needs of residents, and the supply-demand contradiction of medical and health services is becoming increasingly prominent, seriously affecting the healthy development of society [2]. With the continuous intensification of population aging, the total demand for medical services will still maintain a high level. However, due to the imperfect structure of the medical system and the lack of high-quality human resources, the service supply capacity is seriously lagging behind. The growth rate of health technicians and practicing physicians during the same period is clearly unable to meet the annual number of diagnosis and treatment and hospital admissions.

Muscle fatigue is a phenomenon in which the body's muscles are subjected to work activities, resulting in the depletion of energy and substances in the body, affecting muscle energy supply and leading to a decrease

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in muscle output power. Muscle fatigue in patients with limb dysfunction is influenced by many factors, and some fatigue cannot be detected through subjective feelings [3]. If patients neglect their muscle fatigue status for a long time and engage in high-load rehabilitation training, it is likely to cause muscle damage. Therefore, real-time evaluation and monitoring of the patient's muscle fatigue level is necessary. Therefore, based on the current limited rehabilitation resources, high rehabilitation costs, and a large number of people in need of rehabilitation, the author will design a limb rehabilitation system based on deep learning and multi-mode sensing data for patient rehabilitation training and muscle fatigue assessment, in order to improve the efficiency of patient rehabilitation training and ensure the safety of patient rehabilitation training.

2. Literature Review. At present, perception of rehabilitation movements, assessment of limb motor function, and assessment of limb fatigue are the most important and widespread needs in intelligent rehabilitation. Within this landscape, entity relationship extraction methods built upon deep learning primarily encode language units of various scales using low-dimensional word vectors, and then uses neural network models such as convolution and loop to achieve automatic learning and extraction of relevant features. Therefore, the author will use technologies such as the Internet of Things, sensors, and artificial intelligence to study rehabilitation motion perception, limb movement function assessment, and limb fatigue assessment. With the comprehensive effects of these three aspects, it will help optimize existing rehabilitation resources, improve patient rehabilitation outcomes, effectively alleviate the shortage of rehabilitation physicians, and is not limited by time and space, with broad application prospects [4]. Xiuli, L. I. et al. observed the effects of upper limb motor games on cognitive function, upper limb motor function, and daily living activities in stroke patients with mild cognitive impairment. Upper limb motor games can promote the recovery of cognitive function, upper limb motor function, and daily living activities in stroke patients with mild cognitive impairment [5].

Intelligent rehabilitation, as a branch of smart healthcare, can achieve a close integration of engineering and medicine, and has the characteristics of strong knowledge professionalism, complexity, and diversity. During the rehabilitation process, the patient's level of limb motor function will constantly change. Real time assessment of limb function can provide effective information for professional physicians and provide reference basis for the optimization of patient rehabilitation training plans in the future. Swarnakar, R. et al. investigated the potential of artificial intelligence and machine learning in assessing, diagnosing, and creating customized treatment plans for individuals with movement disorders. They utilized wearable sensors, virtual reality, augmented reality, and robotic devices to facilitate accurate motion analysis and implement adaptive neural rehabilitation techniques. Additionally, remote rehabilitation powered by artificial intelligence allows for remote monitoring and consultation. Nonetheless, it is imperative for healthcare professionals to interpret the information derived from artificial intelligence and prioritize patient safety. Despite being in the early stages, the effectiveness of artificial intelligence and ML in rehabilitation medicine will be determined through continued research [6].

In recent years, while machine learning has attracted widespread attention from various sectors of society, it has also made significant breakthroughs in the field of rehabilitation. Compared to traditional criteria for evaluating limb motor function, machine learning based methods for evaluating limb motor function are more real-time and accurate. Tang Jinyu et al.'s study observed the clinical efficacy of rehabilitation care in patients with lower limb fractures and its value in preventing complications. In the experiment, patients with lower limb fractures received rehabilitation care and achieved significant clinical efficacy. The fracture healing time of the patients was significantly shortened, the lower limb motor function and knee joint function were significantly improved, the psychological resilience of the patients was increased, and the incidence of complications was significantly reduced [7]. The study by Yaxian, Z. et al. investigated the effects of different intensities of wearable lower limb rehabilitation robot training on walking function, lower limb motor function, balance function, and functional independence in stroke patients. Wearable lower limb rehabilitation robot training may help improve walking function, lower limb motor function, balance function, and functional independence in stroke patients, and high-intensity training may be more effective [8].

Despite the above research, certain issues persist, including: (1) The limb rehabilitation action recognition method solely employs one type of sensor and fails to merge multi-sensor data for rehabilitating action perception, leading to amplified error noise and reduced precision; (2) Due to the high cost of equipment, reliance on a single data source for measurement, and the inability to ensure accurate motion evaluation, the research falls short in meeting the long-term, high-quality rehabilitation needs of patients; (3) The demanding specifications

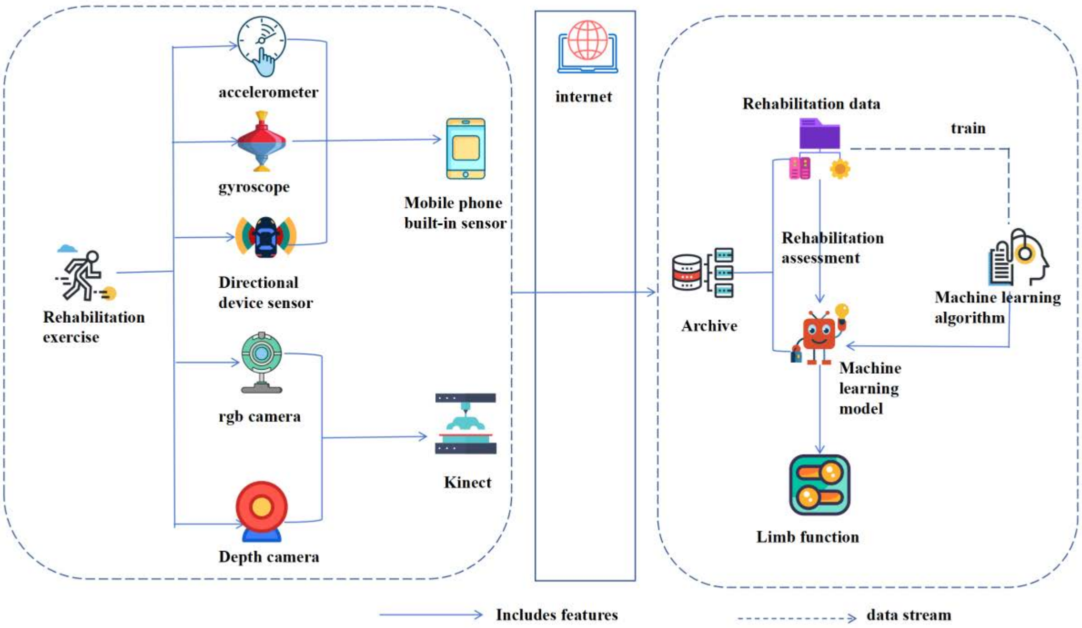

Fig. 3.1: Schematic diagram of limb function evaluation model

for rehabilitation training equipment make it impractical for home use and limit its potential to be accessible to a vast number of patients with limb dysfunction. Therefore, in the context of intelligent rehabilitation, the author collected upper limb rehabilitation movements of patients through low-cost and easily accessible multimodal sensors, and studied the fusion of multimodal sensor data and the perception and evaluation mechanism of rehabilitation movements using machine learning algorithms, achieving low-cost and high-precision rehabilitation action evaluation.

3. Limb function assessment based on machine learning methods . In response to the limitations of existing rehabilitation methods, the author takes multi-modal perception data from rehabilitation training as the research object and explores a limb function evaluation method based on deep learning algorithms. In order to improve the performance of this study, the dynamic time distortion-k nearest neighbor (DTW-KNN) algorithm was selected as a reference to evaluate the LSTM algorithm. Furthermore, the accuracy and efficiency of modeling results between single and multimode data are compared[9]. In addition, the author also conducted a comprehensive discussion on the modeling results.

3.1. Construction of limb function assessment model. A limb function evaluation model that integrates mobile Internet, artificial intelligence, and multi-mode sensors is developed by the author. The structure of this model is divided into two key components: a data collection segment where users directly participate, and a server-based data analysis module. The schematic diagram of the limb function assessment model is shown in Figure 3.1.

Limb movement data is primarily obtained through the built-in inertial sensors found in both mobile devices and Kinect devices. The inertial sensors integrated into mobile devices encompass acceleration sensors, gyroscopes, and directional sensors. On the other hand, Kinect devices utilize RGB cameras and depth cameras for motion sensing purposes. To conduct upper limb movement training, it is necessary for the patient to hold a smartphone equipped with an inertial sensor and select an appropriate standing position in front of the Kinect device before commencing the training session. Upon initiating the training, the smartphone experiences spatial displacement and variations in angles as the patient performs movements with their upper limbs. Real-time data on different upper limb training movements performed by the patient can be monitored and collected

Table 3.1: Display of Original Part Data

a_x	a_y	a_z	ω_x	ω_y	ω_z	Heading angle	Pitch angle	Roll angle	angle
-0.486	0.751	-0.468	-0.04	0.03	0.03	340.6	-48.9	-46.3	1.52
-0.464	0.757	-0.446	-0.04	-0.01	0.02	339.9	-48.7	-46.2	2.44
-0.455	0.763	-0.457	-0.03	0.05	-0.05	340.4	-48.8	-45.9	4.50
-0.464	0.755	-0.467	-0.02	-0.01	0.03	339.5	-48.5	-45.8	4.98
-0.476	0.746	-0.468	-0.03	0.05	-0.05	340.8	-48.9	-46.0	5.97
-0.436	0.770	-0.471	-0.02	0.11	-0.05	339.9	-48.9	-46.2	6.98

through the smartphone's integrated acceleration sensor, gyroscope, and directional sensor [10]. In the inertial sensor mode, the author successfully collected the patient's movement data. Additionally, during upper limb motor training, Kinect somatosensory devices are utilized to capture data on the movement of the patient's limbs. The built-in RGB camera and depth camera of Kinect devices respectively obtain two-dimensional image data and image depth data of patients. Two types of data were preliminarily fused in Kinect, and patient limb joint somatosensory pattern data was obtained. The sensor-collected data from both modes is sent to the server over the Internet for further processing. Following this, the server integrates a variety of machine learning algorithms with diverse pattern data to create several machine learning models for assessing upper limb motions. [11].Once the models are built, inputting the patient's movement data allows for obtaining evaluation results on their upper limb movements. Employing various machine learning models can produce a variety of different outcomes.

3.2. Data preprocessing. Based on the built-in inertial sensors and Kinect of smartphones, the author gathers data on upper limb rehabilitation movements. Subsequently, the collected data on limb rehabilitation is classified and evaluated using DTW-KNN and LSTM algorithms. The inbuilt inertial sensor of the smartphone can determine the sequence data of the patient's upper limb movements by referring to the three-axis coordinate system ofthe phone, including the acceleration values a_x, a_y, and a_z measured by the accelerometer, the angular velocity values ω_x, ω_y, and ω_z measured by the gyroscope when the phone rotates around the three-axis, and the roll angle α, pitch angle β, and heading angle γ measured by the direction sensor. There are a total of 9 types of sequence data. The built-in RGB camera and depth camera of Kinect devices obtain patient limb joint somatosensory mode data. Taking the author's experimental movement of elbow joint flexion as an example, the obtained elbow joint angle . The three joint points of the shoulder, elbow, and hand are all located in the spatial plane, and their range of motion is on the negative half axis of the z-axis in the vector graph. Therefore, the angle between the space vectors ES and EH can be directly used to measure the angle of the elbow joint, and the calculation process is shown in formulas (3.1-3.3):

$$ES = (S_x - E_x, S_y - E_y, S_z - E_z) \tag{3.1}$$

$$EH = (S_x - H_x, S_y - H_y, S_z - H_z) \tag{3.2}$$

$$cos\theta = \frac{ESEH}{|ES||EH|} \tag{3.3}$$

Therefore, the author collected a total of 10 multimodal sequence sensing data, and the raw data collected is shown in Table 3.1.

In this study, there was inevitably a temporal difference in each upper limb movement performed by patients with upper limb dysfunction, so the length of the raw data collected for each upper limb movement was also different. Firstly, the missing data is filled in using anormal distribution, and action sequencesthat are shorter than the specified lengthare extended to ensure that the mean andvariance of the sequence data remain unchanged after interpolation [12]. Secondly, randomly delete action sequences with data entries exceeding

Table 3.2: Action Information

Brunnstrom staging	Action labels	Number of action groups
Phase IV	bad	27
Phase V	in	27
Phase VI	good	27

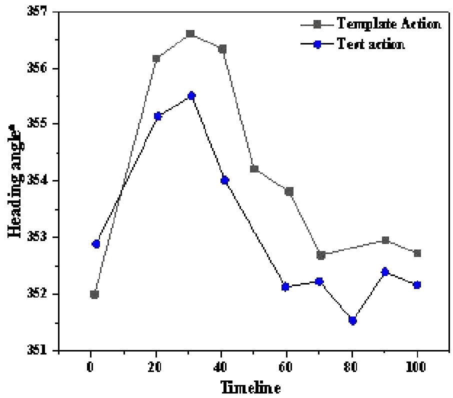

Fig. 3.2: Template Action and Test Action Sequence Trajectory Matching

the specified length, ensuring that the action sequences are of equal length and placed in the LSTM algorithm model. In addition, the collected multimodal sensing data has significant differences in numerical range, and normalization processing is needed to ensure that the data is between 0 and 1, ensuring that it is within the same level. The data normalization is shown in formula 3.4:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{3.4}$$

where X is the raw data, X_{max} and X_{min} are the maximum and minimum values of the data, respectively.

Due to the different rehabilitation stages and functional states of the upper limbs, the quality of rehabilitation actions performed by patients varies. As shown in Table 3.2, the author evaluated the rehabilitation actions of Brunnstrom IV patients as bad, Brunnstrom V patients as medium, and Brunnstrom VI patients as good. 27 sets of actions were collected for each type of data, totaling 81 sets of actions.

3.3. Construction of a limb function evaluation model based on DTW-KNN. The DTW algorithm, also known as dynamic time warping, is a method used to measure the similarity between two time series of different lengths. It uses the idea of dynamic programming to calculate the similarity between two sequences by stretching and compressing time series.

As shown in Figure 3.2, capture the sampling points from 0 to 100 for the template action and test action, and zoom in on some data segments within the red dashed box. The DTW algorithm performs local point-to-point matching on the trajectories of two time series data to minimize the sum of cumulative distances between the two sequences, thereby comparing the similarity between two non equal length sequences. The black curve N represents the template action sequence, the red curve M represents the test action sequence, and $N_1 - N_{15}$ and $N_1 - N_{16}$ represent the data points on the two sequences, respectively. Calculate the Euclidean distance between two data points to obtain the distance matrix C. The correspondence between points in two sequences can be expressed as formula 3.5:

$$f(k) = (f_n(j), f_m(k)) \tag{3.5}$$

Taking the heading angle in Figure 3.2 as an example, $f_n(k)$ and $f_m(k)$ represent the range of heading angle values from -180 ° to 180 °. The value of k is the number of sensor data collected by the patient for a set of rehabilitation training actions, with a range of values from 1 to S. According to the distance matrix C, the cumulative distance matrix D can be obtained. The solution value for the cumulative distance matrix D is $d_f(N, M)$, and the minimum value is $DTW(N, M)$, as shown in formulas (3.6-3.7).

$$d_f(N,M) = \sum_{k=1}^{S} d(f_n(k), f_m(k)) \tag{3.6}$$

$$DTW(N,M) = mind_f(N,M) \tag{3.7}$$

In this study, the acceleration values a_x, a_y, and a_z measured by the accelerometer, the angular velocity values ω_x, ω_y, and ω_z of the three-axis rotation measured by the gyroscope, the angle data α, pitch angle β, heading angle γ measured by the directional sensor, and the angle data collected by Kinect were a total of 10 dimensional sequence data. Therefore, the sum of the distances from each dimension is the distance between two rehabilitation action sequences.

The K Nearest Neighbor (KNN) algorithm is currently a commonly used data classification method. The author selects a K value of 11 and inputs the cumulative distance between two rehabilitation action sequences obtained by the DTW algorithm into the KNN classifier to complete the classification evaluation of patient rehabilitation training actions [13].

3.4. Construction of a limb function evaluation model based on LSTM . Each LSTM cell has 3 inputs and 2 outputs. The inputs include the multidimensional sensing data input x_t

3.5. Experimental setup and evaluation indicators. The author's experiment used word vectors trained by the Word2Vec algorithm for word embedding, with a dimension of 300. Based on prior knowledge, the K parameter was set to 20, the alpha parameter was set to $4e^{-2}$, and the optimal values of other parameters were determined using a grid search algorithm on the dataset. Finally, the optimal results were achieved in the 55th to 60th iteration rounds. The optimal parameter settings for the model are shown in Table 4.2. at the current moment, the LSTM cell output and the cell state h_{t-1} at C_{t-1} the previous moment, and the outputs include the output value h_t and cell state C_t. Currently, the unit status represents the transmission process of information. The LSTM network mainly relies on the unit state C and the current output h for model training. W_f,W_i, W_c, and W_o represent weights, b represents bias terms, σ is the sigmoid function, and tanh is the hyperbolic tangent function, as shown in formulas (3.8-3.9).

$$Sigmoid(z) = \frac{1}{1+e^{-z}} \tag{3.8}$$

$$tanh(x) = \frac{sinh(x)}{cosh(x)} = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{3.9}$$

LSTM cells contain three basic structures, namely output gate, input gate, and forget gate. The three gating units of LSTM each have independent weight matrices and skewing parameters, which can change the connection weight and skewing for each time step data. This design is conducive to avoiding gradient vanishing and explosion, and is suitable for processing long-term multi-dimensional sensing data [14]. The function of the forget gate is to forget unnecessary information and control the magnitude of the forgotten input x_t and the previous hidden layer output h_{t-1}, as shown in formula (3.10):

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{3.10}$$

The function of the input gate is to save new information to the cell state. Firstly, the input gate determines the information in the cells that need to be updated by using an S-shaped function. As shown in formula (3.11):

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{3.11}$$

Table 4.1: Detailed indicators of elbow joint flexion A/B/C completion test movements

index	Class A test action	B-class test action	C-class test action
Accuracy	86.3%	100%	53.2%
recall	78.2%	57.2%	92.3%
Specificity	95.8%	100%	65.2%
F1-Score	82.7%	72.4%	67.6%

After determining the information that needs to be updated, use a tanh function to generate a vector and obtain alternative update content as shown in formula (3.12):

$$C_t' = tanh(W_c[h_{t-1}, x_t] + b_c) \tag{3.12}$$

The final author combines these two parts to obtain a new cell state, as shown in formula (3.13):

$$C_t = f_t * C_{t-1} + i_t * C_t' \tag{3.13}$$

The responsibility of the output gate is to determine the final output content based on the cell state. Firstly, LSTM uses a sigmoid function to determine which part of the cell state to output:

$$o_t = \sigma(W_o[h_t, x_t] + b_o) \tag{3.14}$$

After determining the output part of the cell state, the cell state will be processed by tanh and multiplied by the result of the sigmoid function to obtain the final output result, as shown in formula (3.15):

$$h_t = o_t * tanh(C_t) \tag{3.15}$$

In this study, the input information $x_t = (x_{t1}, x_{t2}, \cdots, x_m)$ represents an n-dimensional feature vector generated by normalizing the original data, which is the multi-dimensional elbow joint flexion motion data obtained by multi-mode sensors. Set the time step to S, take the top S data of the current data to be classified, and obtain $S * n$ dimensional data. The author integrates these data into an input matrix and sends it into the recurrent neural network model. Each time, the data sample $x_t(t = 1, 2, \cdots, s)$ at time t is placed, and a total of S times are placed in the loop. h_{t-1} is the output result of the model at time $t - 1$, which is fed into the hidden layer at time t to obtain the classification prediction result h_t of the action sequence at time t. The LSTM algorithm excels at extracting features from time series and integrating multi-dimensional sensor action data. The simplest method is to treat multi-dimensional sensor action data as a complete multi-dimensional time series. In the author's multivariate time series modeling using multi-dimensional elbow joint flexion motion data as input, updating the state of each time node in the multi-dimensional sensing data is crucial, and a neural network model suitable for multiple input variables is needed. The LSTM algorithm can perfectly solve this difficult problem.

4. Experimental results. In order to evaluate the effectiveness of different pattern data and machine learning algorithms in rehabilitation action classification, it is necessary to compare the accuracy of classification results obtained using different algorithms for different pattern data. This article used DTW-KNN and LSTM algorithms to model the collected data and analyzed the classification results obtained.

(1) The classification of DTW-KNN. It is as follows.

For elbow flexion movements, the overall classification accuracy of DTW-KNN is 71.8%.

The overall classification accuracy of DTW-KNN for elbow flexion and forearm abduction movements is 47.9%.

For shoulder flexion movements, the overall classification accuracy of DTW-KNN is 68.8%. Tables 4.1 to 4.3 provide detailed indicators of the completion of these movements.

Table 4.2: Detailed indicators of elbow flexion and forearm abduction A/B/C completion test movements

index	Class A test action	B-class test action	C-class test action
Accuracy	34.5%	56.8%	0%
recall	56.7%	74.3%	0%
Specificity	63.2%	56%	100%
F1-Score	42.2%	65.2%	0%

Table 4.3: Detailed indicators of shoulder joint flexion A/B/C completion test movements

index	Class A test action	B-class test action	C-class test action
Accuracy	46.85%	92.7%	100%
recall	89.1%	63.4%	63.2%
Specificity	66.5%	90.2%	100%
F1-Score	62.2%	71.6%	77.2%

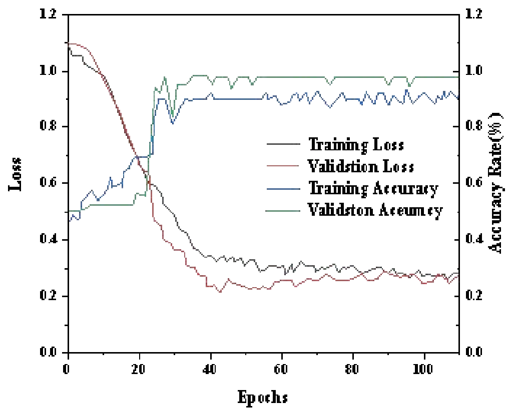

Fig. 4.1: Classification error and accuracy of elbow flexion LSTM neural network model

Table 4.4: Classification Efficiency Analysis of Two Classification Algorithms for the Completion of Three Upper Limb Rehabilitation Actions

Algorithm& Efficiency	action	elbow flexion	Elbow flexion& forearm abduction	Shoulder joint flexion
DTW-KNN Accuracy	71.8%	47.9%	68.8%	
time consuming	127.98s	93.28s	95.18s	
LSTM Accuracy	98.2%	93.3%	95.1%	
time consuming	3.18s	5.41s	3.25s	

(2) LSTM model error and accuracy. Figures 4.1 to 4.3 show the classification errors and accuracy of LSTM neural networks corresponding to elbow flexion, elbow flexion&forearm abduction, and shoulder flexion.

Based on the classification results of three types of upper limb rehabilitation exercises completed by different classification models, as well as the comprehensive efficiency analysis in Table 4.4, from the above analysis, it can be seen that the DTW-KNN algorithm has good overall classification results for the three types of upper

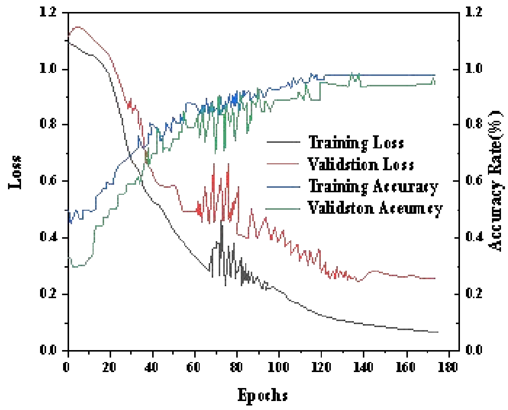

Fig. 4.2: Classification error and accuracy of the LSTM neural network model for elbow flexion and forearm abduction

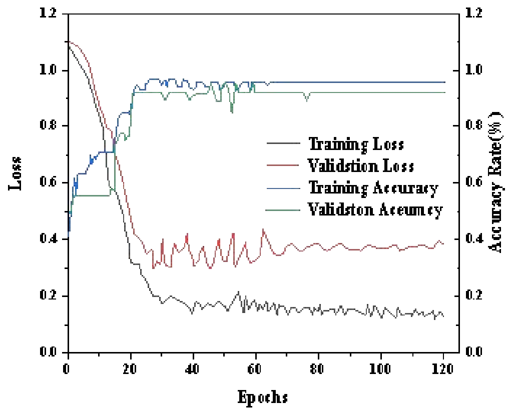

Fig. 4.3: Classification error and accuracy of LSTM neural network model for shoulder flexion

limb rehabilitation movements, but there are differences in accuracy between different rehabilitation movements. The classification accuracy of elbow flexion and shoulder flexion rehabilitation exercises is excellent, but the classification accuracy of elbow flexion and forearm abduction movements is relatively low, only 47.9%. From Table 4.1, it can be seen that the accuracy, recall, and F1 Score of the elbow flexion and forearm abduction movements with completion status C are all 0, indicating that the DTW-KNN classification model cannot accurately classify the movement with completion status C. In addition, among the three types of upper limb rehabilitation exercises, the DTW-KNN classification model provides a more accurate classification of actions with a completion state of B. In elbow flexion, the classification results for actions with a completion state of C are relatively average, while in shoulder flexion, the classification results for actions with a completion state of A are not as good as the corresponding classification results for actions with a completion state of B and C.

The overall fitting of the LSTM neural network model is good. The classification accuracy of LSTM for the above three types of upper limb rehabilitation movements is 98.2%, 93.3%, and 95.1%, respectively. Compared to DTW-KNN, the classification accuracy of neural network models has improved by 26.4%, 45.4%, and 26.3%, respectively. As the number of model iterations increases, the error stabilizes at a relatively low level. In addition, LSTM takes much less time for classification than DTW-KNN, making it more advantageous.

The author takes the common rehabilitation training action of elbow joint flexion as an example, and the results show that the rehabilitation training platform based on multi-mode sensor technology can ensure that patients complete rehabilitation training at home and accurately obtain patient rehabilitation training motion data [15]. In limb function assessment tasks, the evaluation effect of multi-mode sensing data is better than that of single-mode sensing data. The DTW-KNN algorithm performs well in low dimensional data, while in high-dimensional data, the LSTM algorithm performs better in accuracy and time overhead compared to the DTW-KNN algorithm.

5. Conclusion. In response to the current needs of patients with limb dysfunction, with the goal of safety, real-time, non-invasive, and intelligent rehabilitation assessment, and with limb dysfunction patients as the research object, the author uses intelligent perception technology to obtain patient rehabilitation data, fully utilizing the advantages of the data itself, and is committed to achieving rehabilitation training and muscle fatigue assessment for limb dysfunction patients. An efficient and accurate method for evaluating the completion of limb retraining movements is crucial for patients' home rehabilitation. Considering the significant temporal nature of the inertial sensing data collected by the author for limb rehabilitation movements, and the good performance of recurrent neural networks in solving sequence data problems, the author considers using LSTM, which has good performance in processing sequence data, in order to solve practical classification problems. This article provides a detailed explanation of the modeling process for constructing a classification model for action completion based on the inertial sensing data collected from limb rehabilitation movements in this study and the LSTM neural network. In addition, under the guidance of a rehabilitation therapist, the author collected three limb rehabilitation movements: elbow flexion, elbow flexion&forearm abduction, and shoulder flexion under different completion conditions, and conducted DTW-KNN and LSTM comparative experiments, the overall fitting of the LSTM neural network model is good. The classification accuracy of LSTM for the above three types of upper limb rehabilitation movements is 98.2%, 93.3%, and 95.1%, respectively. The classification accuracy of LSTM neural network model has improved by 26.4%, 45.4%, and 26.3% compared to DTW-KNN, respectively. LSTM has a significant advantage over DTW-KNN in terms of classification time, with less classification time.

Real time and accurate assessment of limb function can enable rehabilitation physicians to timely understand the patient's health status, optimize the patient's rehabilitation training plan, and effectively improve the quality of patient rehabilitation. At present, rehabilitation treatment resources are limited, rehabilitation costs are high, and the number of people in need of rehabilitation is huge. In addition, traditional rehabilitation training evaluation methods rely on the professional knowledge of physicians, with strong subjectivity and low accuracy. The completion of the patient's rehabilitation training plan after discharge is not satisfactory, and there is a lack of a comprehensive rehabilitation training evaluation system. In response to this situation, the author has developed a rehabilitation training platform based on multi-mode sensor technology, where patients can receive high-quality rehabilitation training at home according to the rehabilitation plan formulated by physicians. The rehabilitation training platform obtains multi-mode sensing data of patients' rehabilitation through Internet technology, inputs them into the limb function evaluation model, and effectively feeds back the evaluation results of rehabilitation training to patients and doctors in real time, so as to improve the rehabilitation quality and training enthusiasm of patients.

As the effectiveness of patient rehabilitation training continues to improve, the patient's rehabilitation training plan needs to be synchronously optimized. The existing human-machine collaboration methods have poor effectiveness, generally based on single factor considerations, and the efficiency of utilizing expert knowledge is low. They cannot effectively combine rehabilitation medical data with expert knowledge to apply to patient rehabilitation decision support. With the emergence of massive rehabilitation information, clinical diagnosis and treatment doctors and rehabilitation physicians are facing a huge challenge. Clinical diagnosis, treatment, and rehabilitation plans for patients can only be formulated based on subjective personal experience, making it difficult to obtain and reuse past rehabilitation treatment plans, resulting in the waste of medical resources. Therefore, a medical decision support system can be established by combining the massive medical data generated by the rehabilitation industry with the limb movement function results evaluated by patients. Medical decision support systems use cutting-edge technologies such as machine learning and artificial intelligence to conduct in-depth analysis and inference of diverse medical structures and related professional knowledge, thereby assisting doctors in optimizing rehabilitation plans and predicting rehabilitation risks, improving treatment efficiency and service quality for patients.

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