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Article

Intelligent assistive robot design based on big data analysis and biomechanical analysis

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Abstract: To improve the training effectiveness of rehabilitation training for patients with lower limb injuries, the research optimized the long short-term memory network algorithm using convolutional neural network algorithm, and conducted big data analysis on the biomechanics of the human lower limb based on the optimized algorithm. Through the results of big data analysis, the mechanical response mechanism of the human lower limb during movement was studied, and a rehabilitation training intelligent assistive robot that aligns more closely with the biomechanical properties of the human body was designed. An analysis of the biomechanics of the lower limbs of the human body showed that under different exercise states, the muscle strength of the gastrocnemius and soleus muscles in the lower limbs showed similar trends, with the gluteus maximus muscle strength reaching its maximum value in the first 20% of the gait cycle. After optimizing the intelligent assistive robot based on this result, the weekly training efficiency of patients increased to 92.3%. From the above results, it can be concluded that the proposed intelligent assistive robot can significantly improve the rehabilitation training efficiency of patients with lower limb injuries.

Keywords: convolutional neural network algorithm; long short-term memory network; big data analysis; biomechanical analysis; rehabilitation training; intelligent assistive robot

1. Introduction

Lower limb (LL) injuries typically involve damage to the human bones, nerve vessels, and muscle tendons, affecting people's walking and other functions, causing various inconveniences to their normal lives (Cai et al., 2023). Rehabilitation training can promote the recovery of patients' physical functions, improve their daily living abilities, and enhance their quality of life. And accelerate the patient's recovery process, reduce hospitalization time, and lower medical expenses. Rehabilitation training (RT) for patients with LL injuries can improve their recovery speed, shorten their recovery time, and enable them to return to normal life as soon as possible (Wang, Peng, & Hou, 2023). As technology and science advance, various fields are using intelligent technology to help enterprises improve their work efficiency. In the medical field, many scholars have used intelligent assistive robots to provide RT for patients with LL injuries (Ouendi, Hubaut, Pelayo, Anceaux, & Wallard, 2024). However, in many cases, these intelligent assistive robots do not analyze the biomechanics of the lower limbs during human movement, making it impossible to personalize the design of patients' conditions. This results in robots not being able to effectively assist patients in designing personalized training methods, thereby reducing the effectiveness of rehabilitation training. Therefore, it is necessary to optimize the current intelligent assistive robots (Zhao et al, 2022). Convolutional Neural Networks (CNN) algorithm can efficiently obtain feature data from information and improve the accuracy of data analysis (Chen, Seo, & Zhao, 2022). Long Short-Term Memory (LSTM) networks have powerful sequence processing capabilities and can predict data (Kumar, Kumar, & Kumar, 2022). In order to improve the biomechanical analysis effect of intelligent assistive robots on human motion, this study combines CNN algorithm and LSTM algorithm organically, using CNN algorithm to extract features from patients' training images, and then using LSTM algorithm to analyze and predict the extracted feature information, in order to analyze the biomechanical data of human motion. Through the analysis results, the mechanical response mechanism of the lower limbs during human motion is studied, and a robot that is more in line with human biomechanical characteristics is designed. The innovation of the research lies in using CNN-LSTM to conduct big data analysis on the biomechanics of human motion, and optimizing the design of intelligent assistive robots based on the biomechanical analysis results, in order to design robots that are more conducive to patient rehabilitation training.

2. Related works

In order to provide better RT methods for patients with LL injuries, many scholars have designed intelligent assistive robots to assist patients in RT (Lloyd, Jonkers, Delp, and Modenese. 2023). For example, Tao et al. (2024) designed an RT robot to alleviate fatigue in the upper and LLs of Parkinson's disease patients. The robot was tested in practical situations and the results showed that it could alleviate the patient's fatigue by 12.6%. Loro et al. (2023) proposed a gait training robot for the treatment of balance disorders in stroke patients. The outcomes indicated that the robot could improve the treatment effect by 19.3%. In addition, in order to provide better RT methods for people with LL movement disorders, Sun et al. (2022) designed a walking training robot based on control algorithms and compared it with traditional training methods. The results showed that the robot could improve training efficiency by 9.8%. Tsai and Chiang (2023) designed an RT robot based on an adaptive self-organizing fuzzy sliding mode controller to optimize the control accuracy of the LL RT robot. The robot was compared with an unoptimized robot. The comparison results showed that the optimized robot could improve control accuracy by 21.2%. **Table 1** can be obtained by summarizing the above research.

Table 1. Summary of research content.

Author	research contents	Advantage	Insufficient
Tao et al. (2024)	Fatigue relief rehabilitation training robot	Fatigue relief by 12.6%	No biomechanical analysis
Loro et al. (2023)	Gait training robot	The treatment effect has been improved by 19.3%	Long treatment cycle
Sun et al. (2022)	Walking training machine for lower limb movement disorders	Rehabilitation training efficiency increased by 9.8%	Low improvement in training efficiency
Tsai and Chiang (2023)	Optimize the control accuracy of rehabilitation training robots	Control accuracy improved by 21.2%	The rehabilitation effect is not ideal

Big data analysis refers to the process of using advanced analytical techniques and tools to handle and examine varied data sets, in order to reveal the correlations between data, trends in data development, and potential value (Fanelli, Pratici, Salvatore, Donelli, and Zangrandi 2023). LSTM is a big data analysis algorithm widely used for processing sequential data. For example, Pushokhina et al. (2022) proposed an Internet big data analysis technology based on LSTM to deal with the matter of large amount of detection data and difficult analysis in Internet intrusion detection, and used this technology in intrusion detection for testing. The results showed that this technology was able to precisely analyze extensive data on the Internet. The CNN algorithm can accurately extract features from data, and many scholars have used this algorithm to analyze data. For example, Utama et al. (2022) proposed an image recognition approach grounded on CNN algorithm to handle the issue of low recognition accuracy in image recognition, and applied this method for detection in practical situations. The outcomes indicated that the construction recognition error rate of this approach was only 1.386%.

Biomechanics analysis can measure and analyze the mechanical response mechanisms of cells during human movement, in order to design devices that are more in line with human biomechanics (Augustin, 2022). Many scholars have utilized biomechanics for the design of human intelligent equipment, such as, Mercan et al. (2023) conducted an analysis on the biomechanics of RT for patients with tibiofibular joint injuries, and based on the analysis results, a tibiofibular joint injury treatment equipment was designed for performance testing in practical situations. The results showed that the equipment could effectively assist patients in RT.

In summary, although there are currently many intelligent assistive robots, these robots still have the problem of poor robot assisted training effectiveness when providing RT to patients due to the lack of analysis of the biomechanical changes during patient movement. To raise the auxiliary training effect of intelligent assistive robots, the research utilizes the CNN-LSTM algorithm to analyze the biomechanics of the LLs during human movement. By studying the mechanical response mechanism of cells, a robot that aligns more closely with the biomechanical properties of the human body is designed.

3. Intelligent assistive robot based on CNN-LSTM data analysis and biomechanical analysis

3.1. Big data analysis methods based on CNN and LSTM algorithms

With age, various functions of the human body will gradually deteriorate, thereby increasing the risk of falls, strokes, and other serious damage to LL function, which seriously affects people’s lives. So designing an intelligent assistive robot for RT can provide a more effective RT method for patients with LL injuries. The cellular mechanical response mechanism includes cell deformation and changes in stress caused by physical activity, which have different effects on human biomechanics. The changes in human biomechanics are related to the parameter settings of intelligent assistive robots (Elshazly et al., 2023). So, to better carry out RT for the human body, it is needful to use a big data analysis method to analyze the cellular mechanical response mechanism of the LLs of the human body, and then conduct biomechanical analysis. Based on the analysis results, a robot that aligns more closely with the biomechanical properties of the human body can be designed to improve its auxiliary effect and comfort. The LSTM algorithm can be applied to various sequence tasks. By using this algorithm to analyze the various biomechanics of the human LLs, it is possible to predict the various characteristics of the human LLs during motion, thereby constructing intelligent assistive robots (Pastor et al., 2023). The basic steps of using LSTM algorithm for data analysis are shown in **Figure 1**.

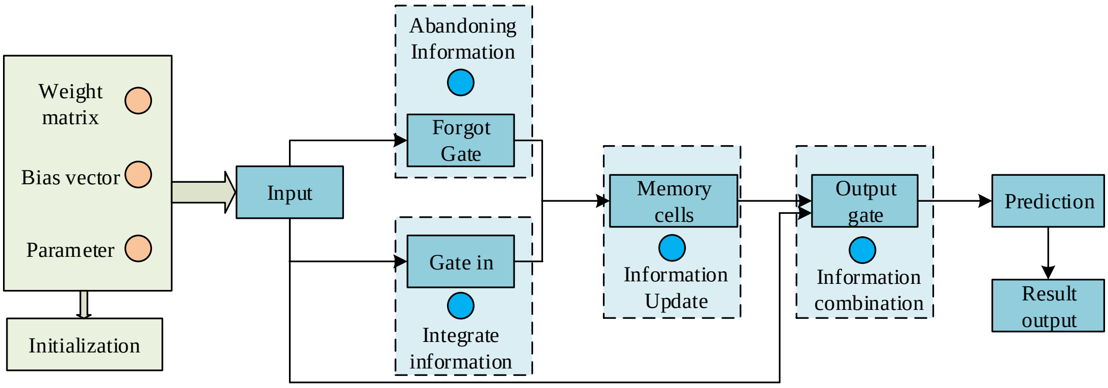


Figure 1. Basic steps of LSTM algorithm.

As shown in **Figure 1**, when the LSTM algorithm analyzes data, it first needs to initialize the network parameters such as the weight matrix (WM) and bias vector of the LSTM. Then, the hidden state (HS) and memory state in each time step are updated through the forget gate (FG), input gate (IG), and output gate (OG) of the LSTM algorithm. The LSTM algorithm repeats the above steps until the entire sequence data is completely processed and outputs the corresponding results. Based on the obtained results, the sequence data is predicted. Among them, the formula for calculating the information retention size in the FG of the LSTM algorithm is shown in Equation (1).

$$f(x) = sigmoid(Wf \times [h(t-1), x(t)] + bf) \tag{1}$$

In Equation (1), $sigmoid$ is the activation function (AF), Wf represents the WM of the FG, $h(t-1)$ is the HS of the previous time step, $x(t)$ is the input of the current time step, and bf is the bias vector of the FG. The output calculation method of IG $i(x)$ is shown in Equation (2).

$$i(x) = sigmoid(Wi \times [h(t-1), x(t)] + bi) \tag{2}$$

In Equation (2), Wi is the WM of the IG, bi is the bias vector of the IG, and the calculation formula for the OG value is shown in Equation (3).

$$o(x) = sigmoid(Wo \times [h(t-1), x(t)] + bo) \tag{3}$$

In Equation (3), Wo is the WM of the OG, and bo is the bias vector of the OG. The calculation method for updating cell state is shown in Equation (4).

$$C(t) = f(x) \times C(t-1) + i(x) \times \tanh(Wc \times [h(t-1), x(t)] + bc) \tag{4}$$

In Equation (4), Wc is the WM of the memory unit (MU), bc is the bias vector of the MU, and $C(t)$ is the state of the MU. The final output value calculation method is in Equation (5).

$$F(t) = o(x) \times \tanh(C(t)) \tag{5}$$

In Equation (5), $F(t)$ represents the final output. However, although the LSTM algorithm can analyze data, it cannot accurately extract feature information, resulting in low prediction accuracy, and further optimization of the LSTM algorithm is needed. The CNN algorithm has powerful feature extraction capabilities and can extract feature information from raw data (Madan & Kumar, 2024). So this study uses CNN algorithm to optimize LSTM algorithm to improve the accuracy of algorithm prediction. The basic process of predicting data using the LSTM algorithm optimized by CNN is shown in **Figure 2**.

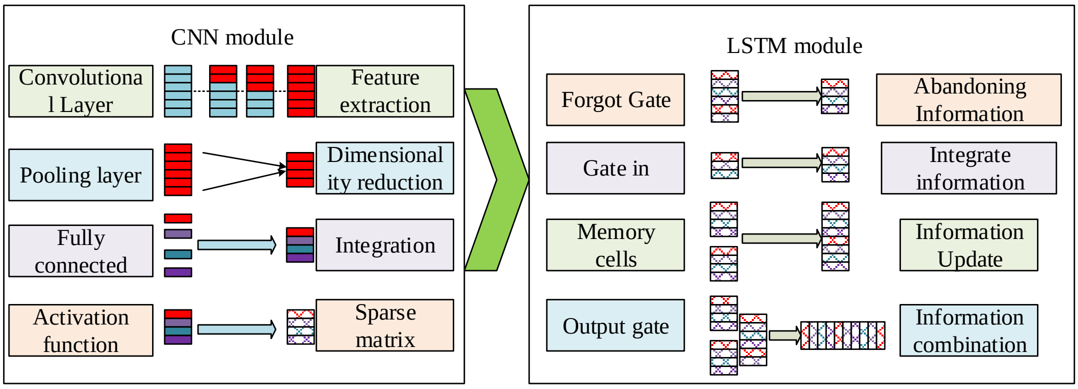


Figure 2. Basic process of CNN-LSTM algorithm prediction.

From **Figure 2**, the CNN-LSTM algorithm is divided into two modules. In the CNN module, the convolutional layer (CL), pooling layer (PL), fully connected layer (FCL), and AF of the CNN algorithm are used to obtain feature details from the input information. The extracted feature information is used as input data in the LSTM module. After repeated iterations of the FG, IG, and OG of the LSTM algorithm, all data sequences are predicted to analyze the LL biomechanics during human motion. In the CNN module, the calculation method for the output information size in the CL is shown in Equation (6).

$$O = (n + 2p - k)/s + 1 \tag{6}$$

In Equation (6), O is the output size of the CL, n is the size of the input information, p is the size of the padding, k is the size of the convolution kernel, and s is the step size. The size of feature information in the PL is shown in Equation (7).

$$O^1 = (n - k)/s - 1 \tag{7}$$

In Equation (7), O^1 is the size of the output feature information of the PL. The data feature information is obtained through the calculation of convolutional and PLs, which facilitates subsequent calculations in the LSTM module.

3.2. Intelligent assistive robot based on CNN-LSTM and biomechanical analysis

At present, many RT intelligent assistive robots cannot accurately analyze the biomechanics of human movement. To address the aforementioned challenges, the study applies the CNN-LSTM algorithm to analyze the cellular mechanical response mechanism of the LLs during human movement. Based on this analysis, the biomechanical changes are analyzed, and the current RT intelligent assistive robots are optimized to accelerate the rehabilitation speed of LL injury patients. The biomechanical analysis steps based on CNN-LSTM algorithm are shown in **Figure 3**.

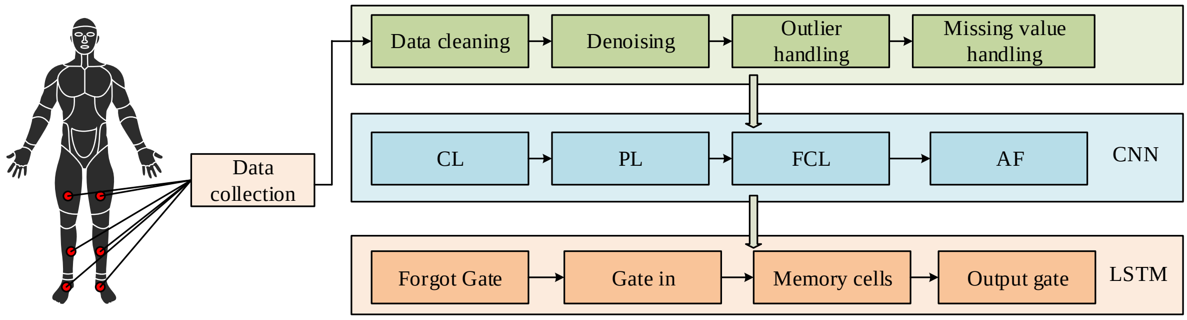


Figure 3. Biomechanical analysis of CNN-LSTM.

As shown in **Figure 3**, when conducting biomechanical analysis, sensors are first worn on the left and right thighs, calves, and feet of the LLs of the human body. The sensors are used to collect the muscle strength of the LLs under different motion states as the dataset of the CNN-LSTM module. The muscle strength can reflect the contractility of muscle cells to analyze the mechanical response mechanism in their cells, thereby obtaining the biomechanical changes of the LLs of the human body. Then, the dataset is cleaned, denoised, outlier processed, and missing value processed to guarantee the precision and completeness of the data. Use the mean filtering algorithm to calculate the average value of each pixel in the image, and use it as the filtered value of that pixel. The specific process is to use a small sliding window to slide on the image, and the pixel values within the window are averaged and assigned to the pixel at the center of the window. This operation is performed by sliding a window across the entire image to achieve the effect of removing noise. Outliers in logarithmic data can be replaced with other data, usually using the mean or median. Finally, the data was normalized using the Min Max normalization method. The normalized expression is shown in Equation (8).

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{8}$$

In Equation (8), X_{min} and X_{max} represent the minimum and maximum values of the input data, respectively. X' is the normalized data, and X is the data before normalization. Afterwards, the CL, PL, AF, and FCL in the CNN structure are used to extract features from the data, and the FG, IG, and OG in the LSTM module are used to capture long-term dependencies in the data. These datasets are used to train the CNN-LSTM model, which is continuously optimized, its evaluation accuracy is improved, overfitting is prevented, and model errors are reduced. Finally, the trained model will be applied to new biomechanical data for biomechanical prediction and analysis. The prediction and analysis results of the model are explained and clarified. The calculation formula for LL muscle strength in the human body is shown in Equation (9).

$$(F+a)(V+b)=(F_0+a)b \tag{9}$$

In Equation (9), F is the magnitude of tension generated when one end of the muscle is released, a and b are unit constants, V is the speed of muscle contraction, and F_0 is the magnitude of tension generated when the muscle contracts. By analyzing the muscle strength of the LLs of the human body, gait recognition can be performed during human movement. The design approach of an intelligent assistive robot based on CNN-LSTM big data analysis and biomechanical analysis is shown in **Figure 4**.

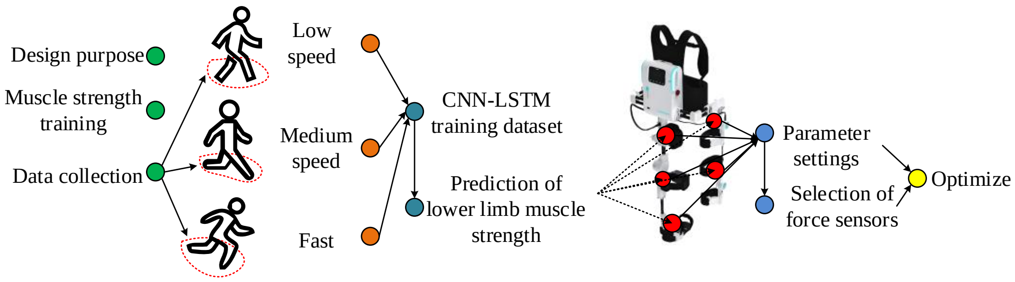


Figure 4. Optimization design of intelligent robots.

As shown in **Figure 4**, when designing an intelligent assistive robot, it is needful to first define the aims of the design for the robot. In this study, the robot is mainly used for training the muscles of the LLs of the human body. Then, various biomechanical data of human motion under different states are collected using sensors as the training dataset for the CNN-LSTM model. The CNN-LSTM model is trained and optimized, and the trained model is used to predict the LL muscle strength of the person to be detected. Grounded on the prediction outcomes, the parameters of the auxiliary robot are adjusted. Appropriate force sensors are selected based on the research objectives, the changes between the target individual's motion state and the surrounding environment are determined, and the overall structure of the robot is designed to ensure that the robot can achieve the expected motion. appropriate robot design materials are selected based on muscle strength prediction results, and materials with good biocompatibility and durability are chosen. Finally, the robot will be used for detection in practical scenarios to evaluate its medical rehabilitation effect on patients with LL injuries, and to test its stability, accuracy, and other performance.

4. Analysis of the actual effect of intelligent assisted robots

4.1. Biomechanics analysis based on CNN-LSTM

To test the advantage of the CNN-LSTM algorithm, in order to test the superiority of the CNN-LSTM algorithm, several commonly used big data analysis algorithms were compared with it. For example, Sparrow Search Algorithm Heden Markov Model (SSA-HMM) algorithm, Grey Wolf Optimizer eXtreme Gradient Boosting (GWO XGBoost) algorithm, and Convolutional Long Short-Term Memory (ConvLSTM) algorithm. These algorithms are all capable of analyzing big data. So, the data analysis performance of the four algorithms is compared to verify the superiority of the CNN-LSTM algorithm. The environmental configuration during the experiment is in **Table 2**.

Table 2. Setup of the experiment environment.

Experimental environment	Index	Type
Hardware environment	CPU	Intel Core i9
	EMS memory	64 GB DDR4 3200 MHz
Software environment	OS	Windows 10
	Python version	Python 4.0
	Python environment	Anaconda 3

The Iris dataset was used as the experimental dataset, which includes Setosa, Versicolour, and Virginica. Comparative experiments were conducted on four algorithms using this dataset to compare their prediction accuracy. The results are shown in **Figure 5**.

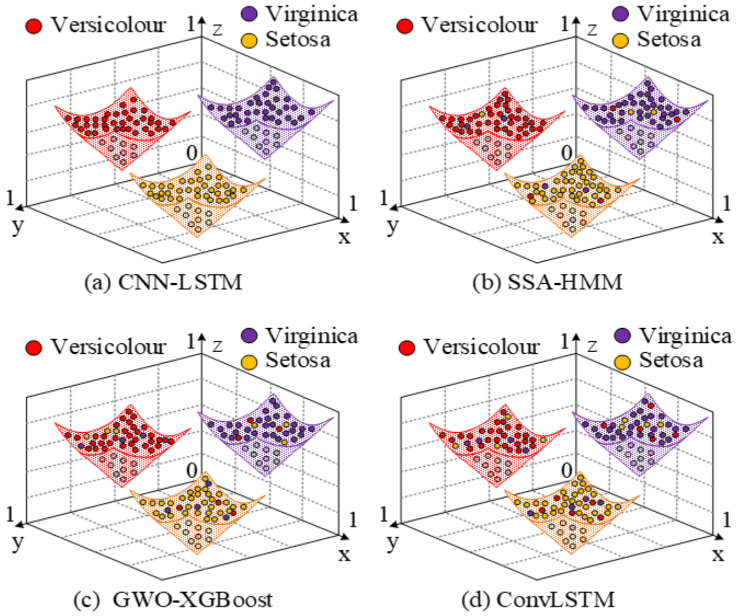
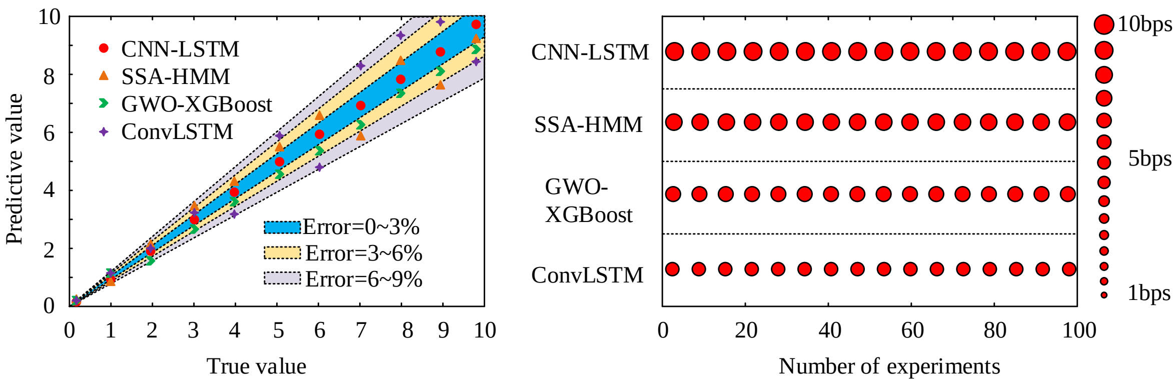


Figure 5. Comparison of prediction performance of algorithms.

As shown in **Figure 5a**, the CNN-LSTM algorithm could accurately predict three types of data in the dataset, and the predicted results were basically the same as the actual results. As shown in **Figure 5b**, the SSA-HMM algorithm still had some errors in predicting three types of data in the dataset. From **Figure 5c,d**, the GWO-XGBoost algorithm and ConvLSTM algorithm had larger prediction errors. The prediction speed and prediction error of the four algorithms were compared, and the outcomes are in **Figure 6**.



(a) Prediction error (b) Algorithm speed

Figure 6. Prediction error and prediction speed.

As shown in **Figure 6a**, the prediction error rate of CNN-LSTM fluctuated between 0% and 3%, with an average error rate of 1.3%. When GOSA-HMM algorithm predicted data, its average prediction error was 2.9%, while the average errors of GWO-XGBoost algorithm and ConvLSTM algorithm were 3.4% and 6.7%, respectively. According to **Figure 6b**, among the four algorithms, the CNN-LSTM algorithm had the fastest prediction speed, with an average speed of 9.5 bps, far higher than other algorithms. From the above outcome, the CNN-LSTM algorithm raised in the study had accurate prediction accuracy and fast computation speed in big data analysis. In order to avoid the risk of algorithm overfitting, the CNN-LSTM algorithm was also subjected to K-fold cross validation. The Iris dataset was still used as the experimental dataset, which was divided into five equally sized subsets (a, b, c, d, e). Four subsets were selected for algorithm training each time, and the remaining subset was used for testing. The verification results are shown in **Table 3**.

Table 3. Cross validation results and computational resource consumption.

Training set	Test set	Calculate accuracy	Calculate error rate	Calculation speed	resource consumption	Space occupancy rate	*p*
a, b, c, d	e	97.4%	2.6%	9.3bps	78.2%	72.2%	0.001
a, b, c, e	d	98.3%	1.7%	9.2bps	76.7%	73.2%	0.002
a, b, d, e	c	96.5%	3.5%	9.3bps	78.1%	74.3%	0.012
a, c, d, e	b	97.4%	2.6%	9.1bps	79.1%	71.5%	0.002
b, c, d, e	a	95.8%	4.2%	9.3bps	78.3%	70.9%	0.001

According to **Table 3**, the CNN-LSTM algorithm has good performance on different test sets, which can avoid the risk of algorithm overfitting. However, the algorithm has a relatively high space occupancy and resource consumption rate during computation. Through t-test, various testing methods of the CNN-LSTM algorithm were statistically analyzed, and the results showed that the statistical results of the algorithm have significant statistical significance ($p < 0.01$). After verifying the predictive performance of the CNN-LSTM algorithm, this algorithm was used to analyze the muscle forces in the biomechanics of the LLs of the human body. The changes in muscle forces in the LLs of the human body were analyzed under slow (1.0 m/s), medium (1.5 m/s), and fast (2.0 m/s) conditions, and the results are shown in

Figure 7.

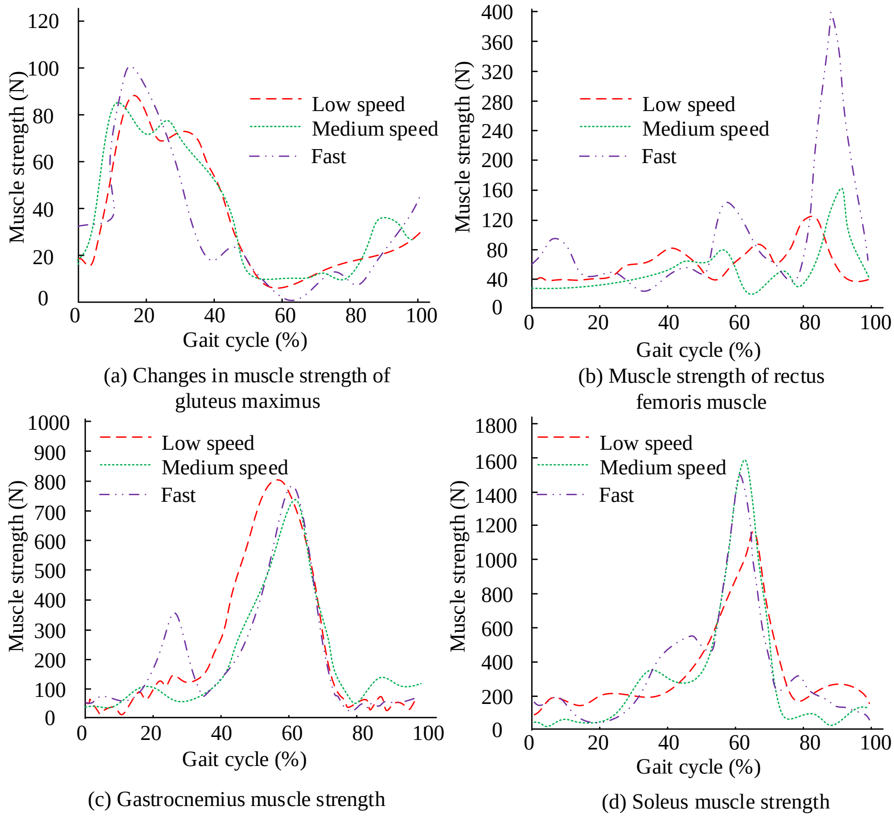


Figure 7. Changes in LL muscle strength.

As shown in **Figure 7a**, the changes in muscle strength of the gluteus maximus muscle varied under different exercise states. In the slow walking state, the maximum muscle strength of the gluteus maximus muscle occurred at 20% of the gait cycle, with a max value of 84.6 N; In the state of moderate speed walking, the muscle force of the gluteus maximus had two peaks, one at 15% of the gait cycle and the other at 30% of the gait cycle, with peak values of 83.2 N and 78.1 N, respectively. In the state of rapid movement, the maximum muscle strength of the gluteus maximus muscle in the LLs of the human body was 102.3 N. From **Figure 7b**, under three different walking states, the change in muscle strength of the rectus femoris muscle was relatively small in 80% of the gait cycle throughout the entire walking cycle. However, in the later stage of rapid walking, the muscle strength of the rectus femoris muscle in the LLs of the human body changed significantly, with a maximum value of 400 N. From **Figure 7c**, the changes in gastrocnemius muscle force were relatively similar under different states, and the time when the maximum value appears was roughly the same. According to **Figure 7d**, the changes in muscle strength of the human LL flounder muscle were roughly the same in the medium and fast walking states, while the maximum muscle strength of the flounder muscle was significantly lower in the slow walking state than in the other two states. From the above experimental results, when designing intelligent assistive robots, the support force of the patient's gluteus maximus muscle should be increased during the first 20% of the gait cycle, while during the 40% to 60% gait cycle, emphasis should be placed on enhancing the support force of the patient's gastrocnemius and soleus muscles. During the 80% to 100% gait cycle, attention should be paid to the support force of the rectus femoris muscle.

4.2. Analysis of the actual effect of intelligent assisted robots

After analyzing the performance of the CNN-LSTM big data analysis model and the biomechanics of human motion, an intelligent assistive robot designed based on the analysis results was analyzed to compare the rehabilitation effects of normal RT and RT using intelligent assistive robots. 200 patients with LL injuries were selected from a certain hospital and divided into two groups with an average of 100 patients in each group. One group would receive RT using the intelligent assistive robot proposed in the study. The other group directly used the normal training methods in the hospital for RT, and analyzed the rehabilitation effects of two different training methods. The inclusion criteria for patients during the experiment are: 1) Stable vital signs of patients; 2) The patient signs an informed consent form; 3) Lower limb injury within 3–6 months; 4) Age between 30 and 45; 5) The type of injury is skeletal injury. The exclusion criteria are: 1) Patients with mental illness or consciousness disorders; 2) History of infectious diseases; 3) Heart, liver, and kidney failure. And during the experiment, a KHG5 infrared sensor capable of detecting human signals was used, with a sampling frequency set to 100 Hz. Perform 7-week auxiliary training on two groups of patients. Firstly, a comparison was made between the Range of Motion (ROM) and muscle strength changes of patients during RT under two different methods, as shown in **Figure 8**.

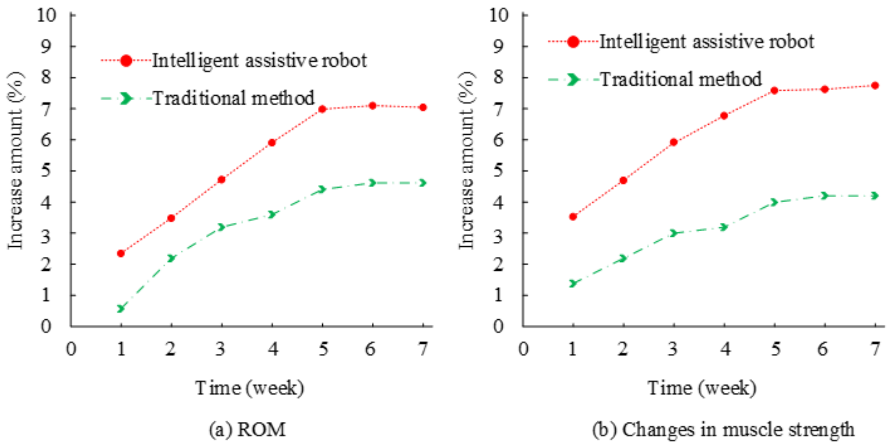


Figure 8. Changes in joint ROM and muscle strength of patients.

According to **Figure 8a**, after using two methods of RT for patients, the ROM of their LL joints continued to improve. However, the improvement in ROM of the intelligent assistive robot during RT was significantly higher than that of the traditional RT method. The intelligent assistive robot could increase the ROM of the patient’s LL by up to 6.9%, while the traditional method could only increase it by up to 3.2% in the same training time. According to **Figure 8b**, after 7 weeks of RT with the proposed intelligent assistive robot, the patient’s muscle strength was improved by 7.3%, which was higher than traditional methods. From this result, it can be concluded that the intelligent assistive robot proposed in the study could significantly improve the ROM and muscle strength of patients’ LL joints after use. Comparing the training efficiency and rehabilitation speed of patients using the two methods, the results are shown in **Figure 9**.

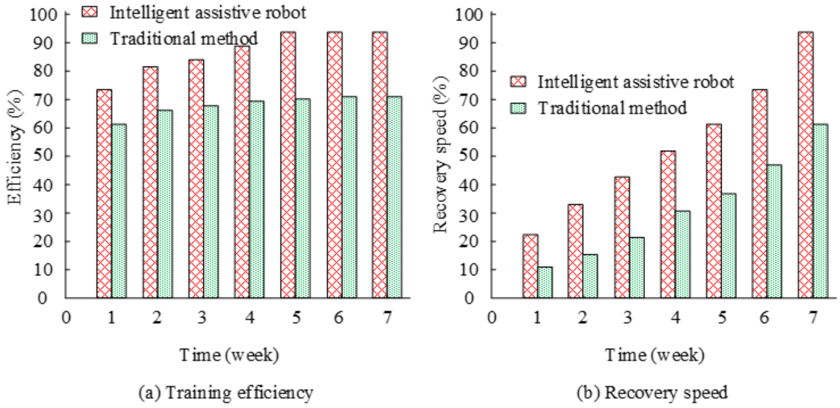


Figure 9. Comparison of training efficiency and rehabilitation speed.

From **Figure 9a**, under both methods, the training efficiency of the intelligent assistive robot proposed by the study for patients with LL injuries was significantly higher than that of traditional methods. After RT with the intelligent assistive robot, the training efficiency continuously increased during the first 5 weeks of training, and in the subsequent time, the training efficiency could reach 92.3%, while the traditional method could only achieve a weekly training efficiency of 61.1%. As shown in **Figure 9b**, compared to traditional RT methods in hospitals, intelligent assistive robots could improve rehabilitation speed every week. The statistical analysis results of patients after 7 weeks of training for the two methods are shown in **Table 4**.

Table 4. Statistical analysis results.

Training methods	Intelligent assistive robot	Traditional method
ROM	6.9 ± 0.12%	3.2 ± 0.01%
Patient's muscle strength improvement	7.3 ± 0.02%	4.1 ± 0.02%
Training efficiency	92.3 ± 0.13%%	61.1 ± 0.01%
Rehabilitation speed	95.6 ± 0.21%	59.1 ± 0.02%
p	0.0001	0.0012

According to **Table 4**, statistical analysis was conducted on the intelligent assistive robot, and the results showed significant statistical significance ($p < 0.01$). From the above results, it can be concluded that the intelligent assistive robot based on CNN-LSTM data analysis and biomechanical analysis proposed in the study could improve the rehabilitation speed of patients.

5. Conclusion

In response to the problem of unsatisfactory training effects of current intelligent assistive robots in RT for patients with LL injuries, this study used the CNN-LSTM algorithm to conduct big data analysis on the biomechanics of patients' LLs during exercise, and optimized the intelligent assistive robot based on the results of big data analysis to design a robot that is more in line with the changes in human biomechanics. Conduct comparative experiments on the proposed CNN-LSTM algorithm, comparing it with SSA-HMM, GWO XGBoost, and ConvLSTM algorithms. The experimental results show that the prediction accuracy of CNN-LSTM algorithm is higher than other algorithms, and the prediction error of CNN-LSTM algorithm is only 1.3%, far lower than the 2.9% of GOSA-HMM algorithm, 3.4% of GWO-XGBoost algorithm, and 6.7% of ConvLSTM algorithm. This result is similar to the experimental results of Alshingiti et al. (2023), and the reason for this result may be that the CNN algorithm in the CNN-LSTM algorithm can accurately extract feature information from human motion images, so subsequent LSTM algorithms can accurately analyze features. The CNN-LSTM algorithm was used to analyze the biomechanics of the LLs of the human body under different motion states. The results showed that in the slow walking state, the maximum muscle force of the gluteus maximus muscle appeared at 20% of the gait cycle, while the change in muscle force of the rectus femoris muscle was relatively small. The muscle forces of the gastrocnemius muscle and the pygmy fish muscle reached their maximum at 50% to 80% of the gait cycle. The trend of muscle strength changes in the LLs of the human body during moderate and fast walking was roughly the same as that during slow walking. The difference was that in fast walking, the muscle strength of the rectus femoris muscle increased significantly between 80% and 100% of the gait cycle. The above results are similar to the analysis results of Hughes and Dai (2023). Through this result, it can be concluded that in the design of intelligent assistive robots, the support force of the patient's gluteus maximus muscle should be increased during the first 20% gait cycle, while the support force of the patient's gastrocnemius and soleus muscles should be strengthened during the 40% to 60% gait cycle. During the 80% to 100% gait cycle, attention should be paid to the support force of the rectus femoris muscle. Through these analyses, various parameters of the intelligent robot should be optimized (Hughes, and Dai. 2023). Further testing was conducted on the optimized robot based on the analysis results, and the results showed that after optimization, the robot was able to increase LL joint mobility by 6.9% and ultimately improve training efficiency to 92.3%, which was much higher than traditional RT methods. From the above results, the intelligent assistive robot proposed in the study could significantly improve the RT effect of patients.

Based on the above analysis results, it can be concluded that during the rehabilitation training of patients with lower limb injuries, the CNN-LSTM algorithm optimizes the parameters of the intelligent assistive robot based on the biomechanical analysis of the patient, in order to assist the patient in better auxiliary training. Through intelligent assistive robots, precise control and repetitive training of various parameters during patient training can be achieved, significantly improving the rehabilitation effect and efficiency of patients. Additionally, intelligent assistive robots can reduce the burden on medical staff and establish personalized rehabilitation training methods for patients through big data analysis methods. However, the CNN-LSTM big data analysis method used in this study has high computational complexity and requires significant resources. In the future, compression techniques such as pruning algorithms can be used to remove unimportant parts of the model, reducing its space occupancy. Alternatively, the weights aggregated by the model can be converted from high-precision floating-point numbers to low precision fixed-point numbers to reduce resource consumption during computation.

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