



Cognitive evaluation model and high-resolution medical images in sports injury rehabilitation under bone density changes

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ABSTRACT

In the study of bone density changes and sports injury rehabilitation, traditional image processing technology lacks accuracy in analysis, rehabilitation assessment methods lack quantitative and systematic analysis, and interdisciplinary comprehensive evaluation is lacking. This paper constructs an innovative cognitive assessment model that combines bone density changes, sports injury rehabilitation, and high-resolution medical image analysis. It uses high-resolution CT (Computed Tomography) images and X-ray images to extract bone density data. It uses image processing technology to remove noise, enhance, and standardize, providing accurate bone density values for subsequent input. GCN (Graph Convolutional Network) can be used to automatically identify and classify images of sports injury sites, extract features of the injured area, record and analyze the patient's physical activities during the rehabilitation stage, and evaluate the recovery process of sports injuries in real time. Combining bone density data with sports injury imaging features, XGBoost (Extreme Gradient Boosting) is used to build a cognitive evaluation model, which conducts a comprehensive analysis of multi-dimensional data and provides personalized rehabilitation evaluation. It can integrate technologies from fields such as medicine, engineering, and computer science to establish an interdisciplinary comprehensive evaluation system, achieve multi-angle and multi-dimensional analysis, and ensure the comprehensiveness and accuracy of the model. The experimental results show that the MAE (Mean Absolute Error) of the GCN in this paper is 0.131 in 10 different injury sites, and the average MSE (Mean Squared Error) is about 0.032, which has higher image analysis accuracy. The average accuracy and R^2 of XGBoost in six different samples are about 0.87 and 0.91, respectively, and the prediction effect of the cognitive evaluation model is apparent.

1. Introduction

The rehabilitation phase of sports injuries is complex and individualized, and rehabilitation assessment faces unique challenges in the context of changes in bone density. Bone density, as a core indicator of bone health, directly affects the speed and effect of recovery from sports injuries [1,2]. With the continuous advancement of precision medicine and image processing technology, personalized rehabilitation assessment based on high-resolution imaging and big data analysis is currently a research hotspot [3,4]. Integrating bone density monitoring and sports injury imaging analysis can achieve multi-dimensional and refined rehabilitation assessment, promote the application of precision medicine in sports medicine, optimize rehabilitation programs, and improve the quality of patient recovery.

In bone density changes and sports injury rehabilitation, existing

research methods lack sufficient accuracy and systematicity [5,6]. Many image processing technologies have limited ability to obtain details, which is particularly prominent in the analysis of high-resolution CT and X-ray images. Noise removal and image enhancement processing are still bottlenecks, and there is a certain deviation in the bone density data extracted from the images [7,8]. The single data source also lacks multi-dimensional support and cannot fully reflect the impact of sports injuries and bone density changes on rehabilitation [9,10].

During the recovery process of sports injuries, some image recognition technologies are used to locate the injured area [11,12]. These methods mainly rely on manual feature extraction and subjective judgment, and lack automated, real-time processing methods, which, to some extent, limit the accurate monitoring of the injury site [13,14]. Rehabilitation assessment also lacks a quantitative and standardized basis, relying too much on the doctor's experience and the patient's

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subjective feelings, and lacks an assessment model that can be dynamically adjusted according to individual differences in patients [15,16].

Considering bone density and recovery from sports injuries, existing methods are also unable to integrate multi-source data. Existing methods rely on single-dimensional data for evaluation and cannot fully integrate imaging data, patient activity records, and historical information [17,18]. These problems make the formulation of rehabilitation programs lack sufficient flexibility and pertinence, the realization of cross-field data fusion, and the construction of accurate multi-dimensional evaluation, which is the key to improving the rehabilitation effect of sports injuries [19,20].

This paper combines bone density data with sports injury image analysis to provide a new cognitive evaluation method for the rehabilitation stage. By using the precise processing of high-resolution medical images, more delicate bone density change information can be obtained, and the recovery progress of sports injuries can be deeply analyzed. Different from the single medical image evaluation, the study introduces image processing technology, GCN, XGBoost, and multimodal data fusion to achieve a comprehensive integration of bone density and injury site, and dynamically evaluate the patient's rehabilitation effect at different times. Using GCN and XGBoost, data of different dimensions are intelligently integrated to construct a personalized evaluation system that adapts to individual differences, which can improve the accuracy of the rehabilitation plan and effectively predict and adjust the patient's recovery process based on real-time monitoring. Refined analysis of big data can achieve precision treatment, provide more targeted rehabilitation suggestions, and improve the patient's recovery speed and quality. This method is used to create a comprehensive research path that integrates medical imaging, bone density analysis, and intelligent evaluation, providing new ideas and methods for future research in the field of sports injury rehabilitation.

2. Related works

Existing studies have focused on single aspects of bone density changes and sports injuries. Some studies have focused on using bone density detection technology [21,22] to assess fracture risk, and on using high-resolution imaging technology [23,24] to analyze the recovery of sports injury sites. Jyoti R discussed the clinical application of various imaging options in sports injuries and emphasized the importance of image-guided surgery in the early return of athletes to activity, outlining their relative advantages and disadvantages in the diagnosis and management of sports injuries [25]. Some studies have proposed bone density assessment methods based on CT images, using image processing technology to improve the accuracy of bone density measurement [26,27]. Dagan N evaluated the automatic fracture risk assessment method based on conventional abdominal or chest CT scans and compared it with traditional fracture risk assessment tools. Osteoporotic fracture CT-based predictors have shown excellent performance in the prediction of major fractures, and CT can be used to automatically assess fracture risk [28]. These methods are difficult to provide comprehensive rehabilitation assessments when used independently, and lack an interdisciplinary comprehensive analysis. Some studies have begun to try to combine machine learning [29,30] with medical image processing technology, but there are still problems, such as high data processing complexity and poor real-time performance; existing research methods cannot meet the real-time and accuracy requirements in sports injury rehabilitation assessment.

Regarding the accuracy of sports injury rehabilitation assessment, some studies have attempted to combine image processing technology, deep learning methods [31,32], and multimodal data analysis [33,34]. Some scholars have proposed a method for sports injury image recognition based on convolutional neural networks, which uses automated feature extraction and classification to achieve rapid diagnosis of injury sites [35,36]. Some scholars have combined bone density data with image analysis and used support vector machine methods to evaluate

the recovery of sports injuries [37,38]. These methods have made some progress in specific areas, but they still face problems such as insufficient model robustness and difficulty in data fusion. There is a lack of effective solutions for the comprehensive analysis of high-resolution medical images and multi-dimensional data. This paper proposes a multimodal fusion model that combines bone density changes, sports injury image analysis, and cognitive evaluation to provide a more accurate and personalized assessment solution for the rehabilitation of sports injuries.

3. Methods

3.1. Bone density data extraction and preprocessing

3.1.1. High-resolution CT image and X-ray image data extraction

All imaging data used in this study were obtained from the clinical databases of collaborating medical institutions and were retrospectively collected using the hospital's Picture Archiving and Communication System (PACS). This study was formally approved by the ethics committee of the relevant medical institution and strictly adhered to the ethical guidelines for medical research. Because this study was a non-invasive, retrospective analysis, and all data were anonymized before use to remove any potentially identifiable patient information, the risk to patient privacy was extremely low and met the requirements for a waiver of informed consent, which was approved by the ethics committee. All data analyses were conducted with full protection of patient privacy.

High-resolution CT images and X-ray images are used to extract bone density data to ensure the accuracy and reliability of the extracted data. Advanced image registration technology is used in the extraction to align multiple-slice images to eliminate errors caused by changes in patient position or different scanning conditions. X-ray image processing uses the Canny edge detection algorithm to extract bone contours, combined with image threshold segmentation technology to separate bone tissue from surrounding soft tissue and effectively obtain the bone area. The image is geometrically corrected and image scale matched in the airspace to ensure the consistency of the two-image data, allowing CT and X-ray image data to be processed under the same standard. The experimental data were derived from clinical imaging data of 12,000 patients with sports injuries, including high-resolution CT images acquired by Siemens Somatom Force equipment and X-ray images acquired by the GE Definium 6500 system to ensure data quality and consistency.

CT images use Hounsfield Unit (HU) to represent the density values of different tissues. Bone density extraction compares the pixel values of the selected bone area with the standard value to obtain bone density information. X-ray images perform quantitative analysis on the gray value of each pixel to extract the bone density value. Using the background noise and artifacts in each image, the local statistical analysis method is used to calculate the mean and variance of the pixel gray value to identify and eliminate noise. The formula is as follows:

$$\mu_{ij} = \frac{1}{N} \sum_{k=1}^N x_{ij}^k \quad (1)$$

μ_{ij} is the grayscale mean of pixel (i, j), x_{ij}^k is the pixel value of the kth sampling, and N is the number of samplings.

In data extraction, in view of the impact of noise on image quality, an adaptive filtering method is applied to reduce the interference of high-frequency noise and artifacts, making the extracted bone density data more accurate. It can process the matching of CT and X-ray images, introduce multi-scale gradient technology, enhance the local features of the image, and improve the resolution and accuracy of the bone area.

3.1.2. Image processing and data standardization

Data standardization is an important step in image processing, which

is used to eliminate the effects caused by equipment differences, shooting angles and image quality fluctuations. Data processing uses adaptive histogram equalization to enhance image contrast and enhance the distinguishability of bone density features in low-contrast areas. The adaptive method processes based on local image features and can effectively avoid information loss that may be caused by global equalization. The key step of the processing is to calculate the pixel grayscale histogram of the local area and stretch it to achieve brightness balance of the entire image. The formula is as follows:

$$h_{ij}^{\text{new}} = \frac{h_{ij} - \mu}{\sigma} \quad (2)$$

h_{ij} is the gray value of pixel (i, j), μ is the local mean, σ is the local standard deviation, and h_{ij}^{new} is the standardized gray value.

The median filtering noise removal algorithm is used to remove random noise in the image and remove the common low-contrast noise in X-ray images. Sort the neighborhood of each pixel and select the middle value as the replacement value to eliminate noise while maintaining edge features. The formula is:

$$\hat{I}_{ij} = \text{Median}\{I_{ij-k,l} | k, l \in \Omega\} \quad (3)$$

$\hat{I}_{ij}$ is the pixel value after denoising, Ω represents the neighborhood range, and (k, l) is the offset of the pixel in the neighborhood.

The range of bone density values is unified into a standard interval after data standardization. The minimum-maximum normalization method is used to further enhance the stability and convergence speed of the model. The standardization formula is:

$$x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (4)$$

x is the original bone density value, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values in the sample, and x_{norm} is the standardized value. The minimum and maximum values are determined based on the statistical results of the training set data to ensure the consistency of the data distribution and prevent information leakage in the test stage.

By using noise removal, enhancement, and standardization, the bone density data has high-quality numerical accuracy and can effectively provide accurate bone density data for subsequent input. This method improves the quality of image data and provides reliable basic data for subsequent GNN input. Table 1 shows the key processing methods for high-resolution CT and X-ray images.

The "Registration accuracy: 0.1mm" in Table 1 is the technical index achieved by the registration algorithm adopted in this study, and it is not a universal standard applicable to all CT devices. This accuracy is achieved through the image registration method used under specific experimental conditions.

3.2. Sports injury images

GCN can be used to automatically identify and classify images of sports injury sites, extract features of the injured area, record and analyze the patient's physical activity during the rehabilitation stage,

and evaluate the recovery process of sports injuries in real time.

3.2.1. Automatic identification and classification of sports injury sites

In the analysis of sports injury images, high-resolution image data is processed, and the significant characteristic areas of sports injuries are extracted through feature extraction algorithms. Convolutional neural networks are used to spatially map the damaged parts in the images, and GCN is used to process the local spatial structure of the image data to accurately identify and classify the damaged areas. GCN can use the topological structure of the graph to process the relationship between different regions in the image and explore the dependency between local regions and global features.

The classification of damaged areas is based on the calculation of damage feature vectors. Considering the node features and adjacency relationships, the graph convolution layer uses the adjacency matrix to aggregate and update the features of each node. The feature representation of each node is $h_i^{(l)}$, and the update rule of graph convolution is:

$$h_i^{(l+1)} = \sigma \left(\sum_{j \in \mathcal{N}(i)} A_{ij} h_j^{(l)} W^{(l)} \right) \quad (5)$$

A_{ij} represents the adjacency relationship between node i and node j , the adjacency matrix is constructed using the K-nearest neighbor algorithm, with image superpixels as nodes and the Euclidean distance and grayscale similarity between nodes as edge weights, ensuring that the graph structure can effectively reflect the spatial and texture correlation of the damaged area, $\mathcal{N}(i)$ represents the set of adjacent nodes of node i , $W^{(l)}$ is the weight matrix of the l layer, and σ is the activation function. This method can obtain the spatial correlation between image regions in the local neighborhood and effectively identify the location and type of motion damage to a certain extent.

Using a multi-layer GCN structure, the detailed features of bone fractures, soft tissue injuries, or joint wear in sports injury images are gradually extracted, and the injury category of each area is output. The feature vector of each injury category is used for subsequent classification tasks to generate injury prediction results. The injury classification results are output through the Softmax layer to predict the probability of the region belonging to different injury types.

Fig. 1 shows the structure of sports injury analysis based on GCN. The input high-resolution image is subjected to noise removal, enhancement, and standardization in the preprocessing layer. The graph convolution layer performs convolution operations on the constructed graph to extract the deep features of the damaged area layer by layer. The convolution of each layer uses activation functions for nonlinear transformation to enhance the learning ability of the model. The output layer comprehensively processes the features of all nodes to obtain the classification results of the damaged area. This structure can effectively obtain local and global features when analyzing sports injuries, provide accurate injury type predictions, and provide a scientific basis for rehabilitation assessment. The analyzable process allows image analysis to have a certain degree of efficiency and accuracy, which helps to track the patient's rehabilitation progress in real time.

Table 1
Key processing methods for high-resolution CT and X-ray images.

Image Type	Processing Steps	Key Methods	Processing Goals
CT Images	Image Registration and Gray Value Extraction	Registration accuracy: 0.1 mm, Threshold: 300 HU	Extract bone density data, eliminate image distortion
X-ray Images	Edge Detection and Threshold Segmentation	Canny edge detection, Threshold: 150	Extract bone contours, separate bone tissue from soft tissue
CT Images	Region Growing Algorithm	Initial seed selection and region expansion	Precisely segment the bone density area, and remove non-bone structures
X-ray Images	Morphological Operations	Circular kernel function, Iterations: 5	Enhance image clarity, extract key regions of interest

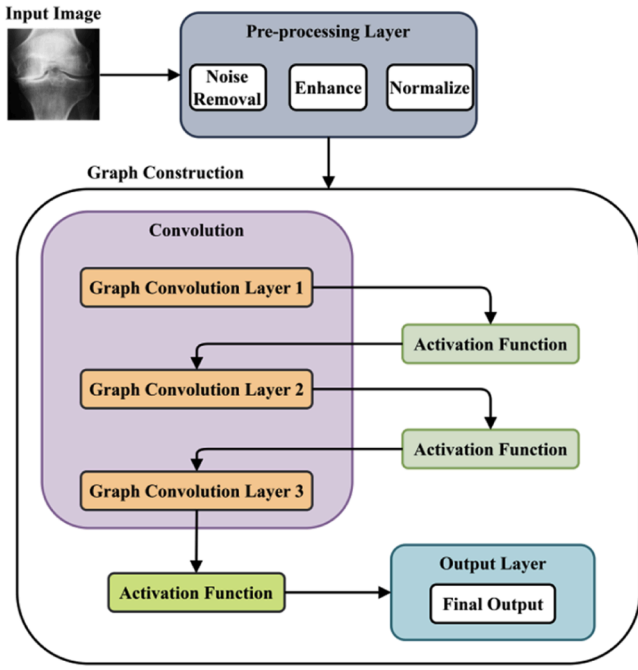


Fig. 1. GCN structure for sports injury analysis.

3.3.2. Physical activity analysis during the rehabilitation stage

During the rehabilitation phase, the patient's physical activity data during the rehabilitation process of sports injuries is combined to analyze the rehabilitation process. A time series model of the patient's activity is constructed using changes in bone density and characteristic changes in the injured area in the image. In each time step, the patient's recovery process from sports injuries is evaluated in real time based on the amount, frequency, and intensity of activity during the rehabilitation period. Based on the degree of injury in the image processing results, combined with historical data and the patient's motor performance, a personalized assessment model is established using the gradient boosting method.

The evaluation indicators of the rehabilitation process involve the recovery of the injured area, the patient's motor recovery level, and the intensity of the activity. These factors are derived by fusion of image features and motion data, and the evaluation results of each rehabilitation stage are obtained by a weighted sum. The motion activity data is $A(t)$, the recovery of the injured area is $R(t)$, and the output of the evaluation model can be expressed as:

$$\text{Evaluation}(t) = \alpha A(t) + \beta R(t) \quad (6)$$

α and β are adjustment parameters, and the weights are automatically adjusted according to the different stages of rehabilitation. The sliding window algorithm is introduced in the evaluation to update the time series data in real time, and the weights and parameters of the evaluation results are adjusted using the patient's current status and historical information; The balance between sliding window size selection and model accuracy and real-time performance is optimized according to the frequency of data changes during the patient's recovery process.

The gradient boosting algorithm is used to predict and correct the recovery progress at each time point. The gradient boosting algorithm is based on residual learning, continuous iterative training, and adjustment, and gradually reduces the prediction error. This approach can optimize the accuracy of rehabilitation assessment and avoid distortion of rehabilitation assessment caused by changes in external factors while processing real-time data.

The organic combination of image analysis and physical activity data can realize dynamic monitoring of the patient's rehabilitation stage. The

evaluation results can help personalize the rehabilitation plan and provide a scientific recovery path for sports injuries.

3.3. Construction of cognitive evaluation model

Combining bone density data with sports injury imaging features, XGBoost is used to build a cognitive evaluation model, which provides personalized rehabilitation evaluation through comprehensive analysis of multi-dimensional data.

3.3.1. Feature fusion and comprehensive evaluation framework

Building a cognitive assessment model requires deep integration of bone density data and sports injury imaging features. Bone mineral density data and sports injury image features are presented in different ways. Bone mineral density data are standardized as continuous numerical variables; the image features are structured data extracted by an image analysis algorithm, showing a high-dimensional vector. A weighted feature combination can be used to establish an input framework for multidimensional data. A weighted linear combination was used to integrate the bone mineral density and imaging features to avoid the excessive influence of a single feature on the performance of the final model. The bone density data is x_{bone} , and the image feature is x_{image} . The fused features can be expressed as:

$$x_{\text{fusion}} = \lambda_1 x_{\text{bone}} + \lambda_2 x_{\text{image}} \quad (7)$$

In this paper, λ_1 and λ_2 are non-negative weight coefficients, which satisfy $\lambda_1 + \lambda_2 = 1$. The value range is optimized and determined within the interval of [0,1] by cross-validation to ensure the balanced fusion of bone density and image features. The fusion feature vectors ensure a balanced use of BMD and imaging information.

The fused features are used for training, and a comprehensive evaluation framework is adopted for these multidimensional data to consider the time series characteristics of bone density and injury recovery, as well as the stage differences of motor ability recovery. The goal of the framework is to comprehensively analyze the multidimensional characteristics of individuals and provide personalized rehabilitation evaluation results for patients.

3.3.2. Model training and personalized assessment

In the training phase, an accurate and efficient cognitive assessment model is constructed, which can output the patient's rehabilitation assessment results based on the input features. A learning framework based on gradient boosting is used to optimize the weighted loss function to improve accuracy and stability. The predicted value is $\hat{y}_i$, the true label is y_i , and the loss function can be expressed as:

$$L(\hat{y}_i, y_i) = \sum_{i=1}^n (\hat{y}_i - y_i)^2 + \gamma \sum_{t=1}^T \left(\sum_{i=1}^n (w_{i,t})^2 \right) \quad (8)$$

γ is the regularization parameter, which is used to control the complexity of the model. In this experiment, 0.5 is taken. $w_{i,t}$ is the parameter weight of each tree, and T is the total number of trees. The loss function uses the balance prediction error and model complexity to avoid overfitting and effectively improve the performance of the model on unknown data.

XGBoost is used for step-by-step optimization, continuous iterative training, and adjustment of the residuals of each round to gradually improve the prediction accuracy. During each round of training, the current residual and data deviation are calculated, and the prediction output is updated; the prediction of the t th round is $f_t(x)$, and the model update rule is:

$$f_{t+1}(x) = f_t(x) + \eta \cdot \arg\min_h \sum_{i=1}^n L(y_i, f_t(x_i) + h(x_i)) \quad (9)$$

η is the learning rate, $h(x_i)$ is the current iterative learner, and $\arg\min_h$ represents the optimization process of minimizing the current loss

function. The model can gradually reduce the residual in each update and improve the accuracy of the prediction results.

The model can evaluate the patient's rehabilitation progress in real time based on their bone density, injury characteristics, and historical data, and can also provide a personalized rehabilitation plan. The personalized assessment results can recommend the appropriate amount of exercise, treatment methods, and rehabilitation goals based on the specific situation of each patient, accurately guiding every step of the rehabilitation process.

The model can also perform transfer learning based on different patient groups to ensure the accuracy of the assessment and make adaptive adjustments to the model. The assessment weights and strategies can be dynamically adjusted based on the patient's age, gender, injury type, and other characteristics, so that the model has the ability to conduct personalized assessments and can also improve the applicability among different patient groups.

The constructed cognitive evaluation model can realize real-time and accurate monitoring and evaluation of sports injury patients during the rehabilitation process. The rehabilitation progress and related indicators of each patient can be fed back in the first place, helping doctors and patients make more scientific treatment decisions and optimize rehabilitation effects.

Fig. 2 shows the application structure of XGBoost in bone density changes and sports injury rehabilitation assessment. The input data includes bone density data and sports injury image features, which are sent to multiple decision trees for training. Each tree consists of multiple nodes, which segment the features of the data and make predictions step by step. The leaf nodes of each tree output preliminary prediction results, which represent the evaluation of different stages of rehabilitation. The prediction results of multiple trees are finally integrated to generate a comprehensive evaluation result, providing personalized rehabilitation advice. The output represents the model's overall prediction of the patient's rehabilitation process, helping doctors to develop more accurate treatment plans. This structure reflects XGBoost's advantages in processing multidimensional data and making complex predictions, and can provide highly accurate personalized evaluations when combined with bone density and sports injury imaging data.

3.4. Establishment of an interdisciplinary comprehensive evaluation system

It is possible to integrate technologies from fields such as medicine, engineering, and computer science to establish an interdisciplinary

comprehensive evaluation system, achieve multi-angle and multi-dimensional analysis, and ensure the comprehensiveness and accuracy of the model.

3.4.1. Interdisciplinary data fusion strategy

The data and technology of different disciplines, such as medicine, engineering, and computer science, can be deeply integrated to achieve a multi-dimensional analysis of comprehensive evaluation. The key in this process is to use reasonable feature mapping to enable seamless connection of data between disciplines. Medical data, such as bone density and patient health records, are standardized using professional medical knowledge and converted into quantitative indicators. Engineering data, such as force analysis of sports injury sites and dynamic assessment data during rehabilitation, are obtained using physical modeling and sensing technology and converted into precise numerical data. Computer science provides efficient data processing and analysis methods, processing the whole process from image to feature extraction, and data in all fields are standardized and weighted through a well-designed algorithmic framework.

Various types of feature data can be processed by weighted averaging. The feature data in different fields are x_{med} , x_{eng} , and x_{comp} , respectively, and the weighted sum can be expressed as:

$$x_f = q_1 x_{med} + q_2 x_{eng} + q_3 x_{comp} \quad (10)$$

q_1 , q_2 , and q_3 are weight coefficients for data in different fields. The fusion data set can fully reflect the patient's bone mineral density changes, injury site, and recovery, and provide a more comprehensive and precise input. Interdisciplinary data fusion gives models the ability to analyze from multiple perspectives and eliminates possible limitations and deviations from a single data source.

3.4.2. Multidimensional modeling of interdisciplinary evaluation system

Interdisciplinary technology is not limited to data fusion, but also requires the use of methods and theories from different disciplines to establish a comprehensive model to ensure the comprehensiveness and accuracy of the evaluation. The model construction takes into account the characteristics of the data in each field and selects different weighting strategies and evaluation methods. A comprehensive evaluation is conducted from multiple dimensions, such as time series, spatial characteristics, and individual differences of patients, comprehensively considering bone density, injury recovery, and patient history information.

A hierarchical modeling approach is adopted to enhance the flexi-

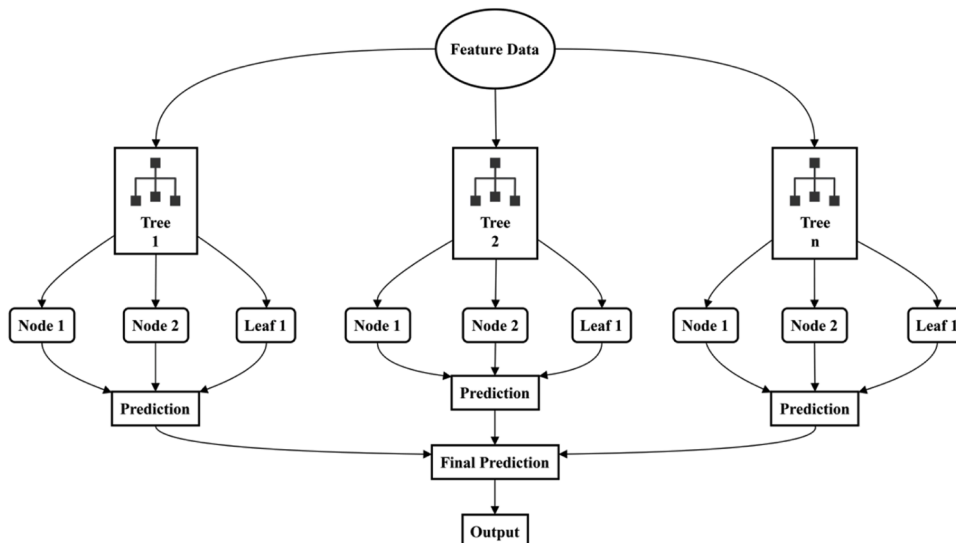


Fig. 2. XGBoost model structure: bone density and sports injury rehabilitation assessment.

bility and adaptability of the model in different dimensions. In the prediction of the change trend of bone density, time series analysis is introduced to predict the trend of bone density data of each patient. The bone density of the patient at time t is b_t , and the change trend can be expressed by the following formula:

$$\Delta b_t = ab_{t-1} + \beta x_t + \epsilon \quad (11)$$

The evaluation of sports injury recovery uses a spatial analysis model to analyze the recovery process based on the patient's movement trajectory and rehabilitation data. The recovery speed of the injured area is closely related to the patient's activity. The spatial analysis method is used to combine the movement trajectory data and bone density change data to calculate the key points in the recovery process. This method can reflect the dynamic changes of patients in rehabilitation in real time and provide decision support.

Taking into account individual differences among patients, the personalized evaluation based on the patient's historical data is integrated, and the age, gender, weight, and other characteristics of different individuals are weighted. The evaluation strategy can be automatically adjusted to make the evaluation results between different groups more applicable and accurate. The personalized evaluation formula is as follows:

$$\hat{h}_i = f(\lambda_1 x_{med}, \lambda_2 x_{eng}, \lambda_3 x_{comp}, \theta_i) \quad (12)$$

$\hat{h}_i$ is the evaluation result of the i th patient, θ_i is the patient's personalized feature vector, and this formula enables the model to provide customized rehabilitation plans based on the different characteristics of the patients.

The establishment of this comprehensive assessment system does not rely solely on the technology of a single discipline, but rather utilizes cross-disciplinary technology integration to give full play to the advantages of data and methods in each field to provide comprehensive and accurate rehabilitation assessments. The data and models can be continuously optimized, and the system can adapt to more complex patient groups, provide more intelligent and personalized rehabilitation assessment solutions, and promote the development of precision medicine and personalized treatment in the field of sports injuries.

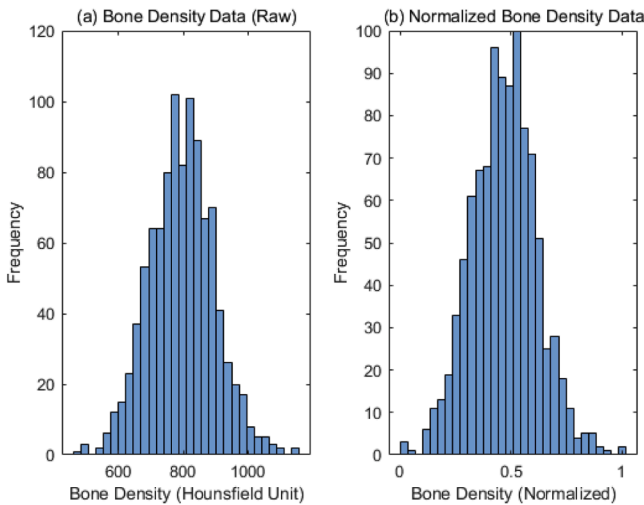


Fig. 3. Comparison of bone density value distribution before and after data standardization.

4. Method effect evaluation

4.1. Standardization of bone density data and comparison of images before and after bone density extraction

Fig. 3 shows the distribution changes of bone density data before and after standardization. The histogram on the left shows the original bone density data. The distribution of the Hounsfield unit data is relatively scattered, showing large fluctuations and a wide range of values. This shows that the original data contains bone density values in different ranges, and the numerical deviation is large. The histogram on the right is the standardized bone density data, and all data are compressed to the $[0, 1]$ interval, showing a more concentrated and uniform distribution. Standardization ensures the consistency of the data, eliminates the scale differences between different bone density values, and enables better comparison and analysis of the data in subsequent processing. The standardized data helps reduce bias in training and improve prediction accuracy.

Fig. 4 shows the comparison of the original CT image and X-ray image after different processing steps. In the original CT image, there is noise and unclear areas, which affect the accurate extraction of bone density. The noise of the denoised CT image is effectively suppressed, and the main details in the image are clearer, which is helpful for subsequent analysis and feature extraction. After contrast enhancement, the brightness and contrast of CT images and X-ray images are improved, and the features of bone density and damaged areas are more prominent. The standardized image values are normalized to a specific range, which is smaller than the original image, ensuring data consistency and providing accurate input data for subsequent models. These processing steps effectively improve the image quality and provide reliable basic data for the assessment of bone density changes and sports injury rehabilitation.

4.2. Assessment of the correlation between bone density changes and sports injury rehabilitation

In the evaluation of the correlation between bone density changes and sports injury rehabilitation, the patient's bone density data and sports injury recovery data are extracted to build a correlation model between the two. The changes in bone density of each patient and the corresponding rehabilitation progress are systematically recorded, and the bone density data are standardized to ensure the consistency and comparability of various data.

Fig. 5 shows a scatter plot comparison of the relationship between bone density changes and rehabilitation progress using the imaging analysis method in this paper and the traditional imaging analysis method. Figure A is the image analysis method used in this paper, which shows the linear correlation trend between bone density changes and rehabilitation progress. The data points show a certain positive correlation. When bone density increases, the rehabilitation progress gradually improves, and the data points are distributed more concentratedly, which is in line with the expected law of rehabilitation progress. Figure b shows the results of the traditional image analysis method. The distribution of data points is relatively scattered, showing a relatively low correlation. The relationship between the rehabilitation process and bone density change is not as significant as that of the method in this paper. By comparing the scatter plots of the two, it can be intuitively seen that the image analysis method in this paper is superior to the traditional method in image analysis effect, providing more reliable data support for the evaluation of the rehabilitation process.

4.3. Comparison of image analysis accuracy

The image analysis accuracy uses two evaluation indicators, MAE and MSE, to compare and analyze the GCN image processing algorithm used in this paper with the traditional GNN (Graph Neural Networks)

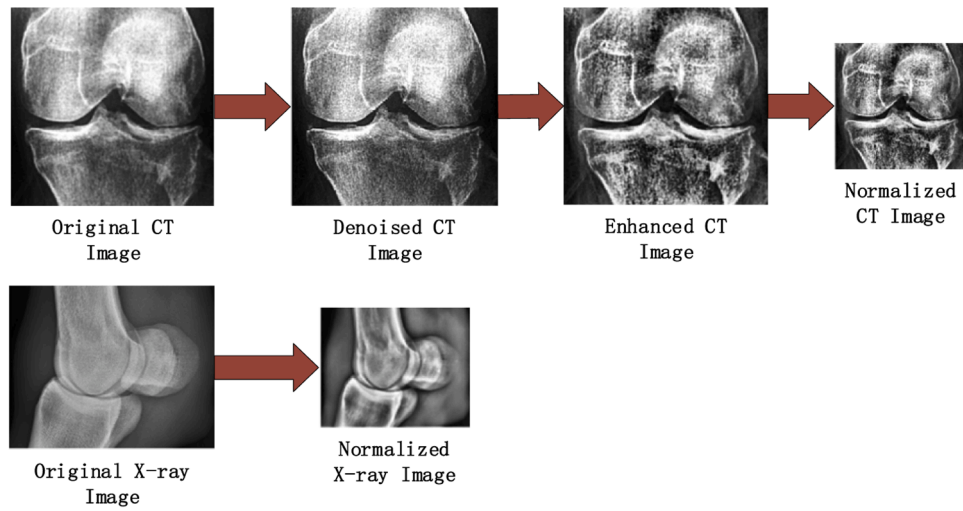


Fig. 4. Comparison of images before and after bone density extraction.

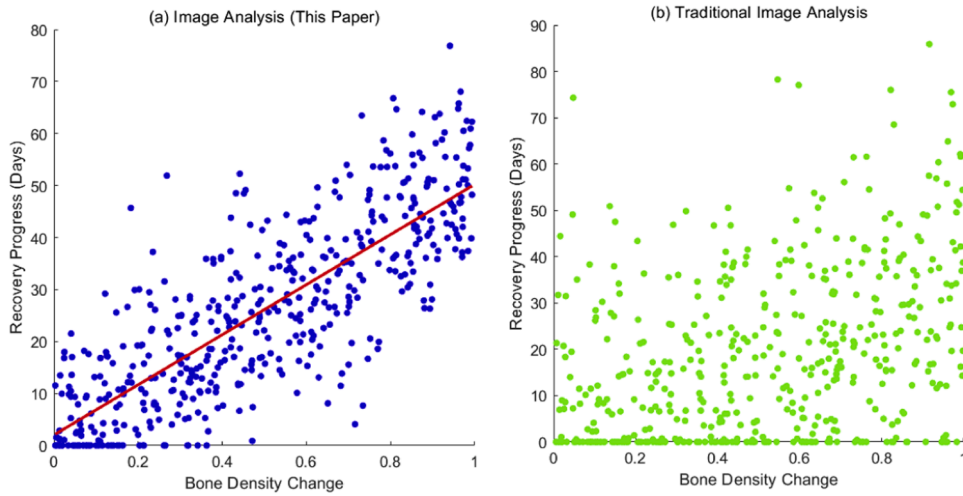


Fig. 5. Correlation between bone density changes and rehabilitation progress of different imaging analyses.

and GAT (Graph Attention Network) methods. The three algorithms were applied to imaging data of multiple injury sites, and their respective prediction results were recorded. All images went through the same preprocessing process to ensure the rigor of the analysis and were

evaluated on the same data set to eliminate the interference of external variables on the results.

The values of MAE and MSE can be used to compare the prediction accuracy of each method at different injury sites, reflecting the

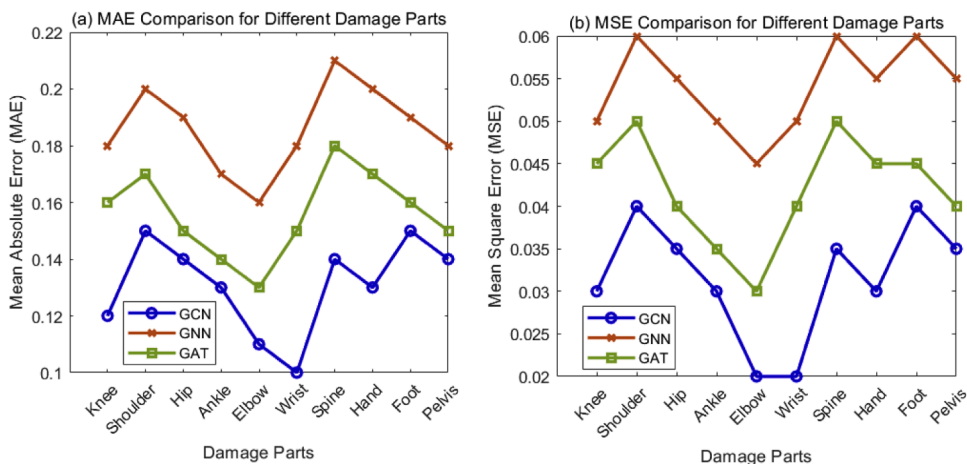


Fig. 6. Comparison of image analysis accuracy.

analytical ability of the area with significant bone density changes and the edge of the injury. MAE evaluates the absolute error between the predicted value and the true value, while MSE takes into account the square of the error and can more sensitively reflect the impact of large errors. These indicators can comprehensively evaluate the performance of GCN in complex image parsing tasks and verify its advantages in image analysis accuracy compared to traditional methods.

Fig. 6(a) shows the comparison of the MAE index of the three algorithms, GCN, GNN, and GAT, at different damage sites. The horizontal axis is 10 damage sites. The GCN algorithm shows obvious advantages at all damage sites, with an average MAE of 0.131, which is lower than GNN and GAT. GCN can provide more accurate predictions in these areas, and its performance in multiple injury sites is generally better than other algorithms, reflecting its high efficiency in image analysis. Fig. 6(b) shows the comparison of the three algorithms in terms of MSE indicators. Similar to MAE, GCN has generally lower MSE values in various injury sites. The average MSE value of GCN in all parts is about 0.032, which is lower than the MSE of GNN and GAT, verifying its lower error and higher accuracy in image analysis. The results of the two indicators show that GCN can better obtain injury characteristics when processing high-resolution medical images and improve the reliability of rehabilitation assessment.

4.4. Evaluation of the cognitive evaluation model

According to the actual rehabilitation data of patients, the cognitive evaluation model was evaluated using indicators such as accuracy and R^2 , and the XGBoost in this paper was compared with the traditional CatBoost (Categorical Boosting) and LightGBM (Light Gradient Boosting Machine) to verify its improvement in predictive ability.

Fig. 7 shows the comparison of the accuracy and R^2 values of different models in six different samples. The columns represent the accuracy of the three methods XGBoost, CatBoost, and LightGBM, and the other three lines show the R^2 value of each method. XGBoost showed high accuracy and R^2 values in all samples, with average accuracy and average R^2 of approximately 0.87 and 0.91, respectively. XGBoost's accuracy and R^2 values were ahead of the other two methods, showing its advantages in data processing and model fitting. CatBoost and LightGBM have certain performance in the sample, but the overall performance is slightly inferior. In terms of R^2 value, XGBoost always maintains a high stability and has a strong advantage in data fitting ability. XGBoost performs better than Categorical Boosting and LightGBM, showing its strong predictive ability in multidimensional data analysis and rehabilitation evaluation.

5. Conclusions

This paper establishes a new cognitive evaluation model that combines bone density changes, sports injury rehabilitation, and high-resolution medical image analysis, and combines multidisciplinary technology to systematically solve the evaluation problems in the process of sports injury rehabilitation. By innovatively integrating methods from medicine, engineering, and computer science, a comprehensive rehabilitation assessment system can be constructed, which can realize intelligent analysis of the entire chain from data collection, processing, to prediction. The core innovation of the model lies in combining bone density data with sports injury image features, using efficient image processing technology and GCN and XGBoost to accurately extract the features of the injury area, and based on these features and the behavioral data of the patient during rehabilitation, a cognitive evaluation system is established to provide personalized and dynamic rehabilitation assessment. The evaluation results show that the model proposed in this paper has significant improvements in accuracy and predictive ability. In terms of the combination of image analysis and cognitive evaluation models, the use of GCN and XGBoost methods can achieve better results in complex data processing. Interdisciplinary data fusion

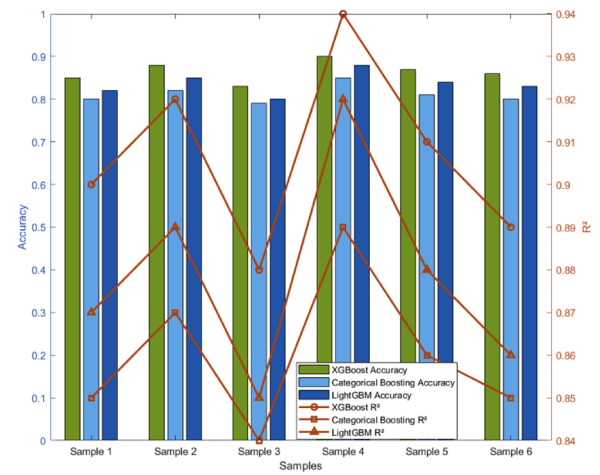


Fig. 7. Comparison of accuracy and R^2 of different models.

enhances prediction accuracy and ensures the targetedness and optimization of rehabilitation programs. In the future, with the increase in data volume (such as real-time physiological and motion data collected by wearable devices, sharing of multi-center clinical imaging databases, electronic health records of patients' long-term follow-up, etc.), and continuous optimization of the model, this research is expected to further improve its universality and accuracy, and provide effective support for a wider range of sports injury rehabilitation fields.

CRediT authorship contribution statement

Wenping Li: Writing – original draft, Validation, Methodology, Data curation. **Zhiming Gu:** Writing – review & editing, Software, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

- [1] Gennarelli SM, Brown SM, Mulcahey MK. Psychosocial interventions help facilitate recovery following musculoskeletal sports injuries: a systematic review. *Phys Sport* 2020;48(4):370–7.
- [2] Song H, Montenegro-Marin CE. Secure prediction and assessment of sports injuries using deep learning based convolutional neural network. *J Ambient Intell Humaniz Comput* 2021;12(3):3399–410.
- [3] Clarsen B, Bahr R, Myklebust G, et al. Improved reporting of overuse injuries and health problems in sport: an update of the Oslo sport trauma research center questionnaires. *Br J Sports Med* 2020;54(7):390–6.
- [4] Derman W, Badenhorst M, Blauwet C, et al. Para sport translation of the IOC consensus on recording and reporting of data for injury and illness in sport. *Br J Sports Med* 2021;55(19):1068–76.
- [5] Richmond SA, Donaldson A, Macpherson A, et al. Facilitators and barriers to the implementation of iSPRINT: a sport injury prevention program in junior high schools. *Clin J Sport Med* 2020;30(3):231–8.
- [6] Li B, Xu X. Application of artificial intelligence in basketball sport. *J Educ Health Sport* 2021;11(7):54–67.
- [7] Timpka T, Spreco A, Dahlstrom O, et al. Suicidal thoughts (ideation) among elite athletics (track and field) athletes: associations with sports participation, psychological resourcefulness, and having been a victim of sexual and/or physical abuse. *Br J Sports Med* 2021;55(4):198–205.
- [8] Tee JC, McLaren SJ, Jones B. Sports injury prevention is complex: we need to invest in better processes, not singular solutions. *Sports Med* 2020;50(4):689–702.
- [9] Orchard JW, Meeuwisse W, Derman W, et al. Sport medicine diagnostic coding system (SMDCS) and the orchard sports injury and illness classification system (OSIICS): revised 2020 consensus versions. *Br J Sports Med* 2020;54(7):397–401.
- [10] Palmer D, Cooper DJ, Emery C, et al. Self-reported sports injuries and later-life health status in 3357 retired Olympians from 131 countries: a cross-sectional survey among those competing in the games between London 1948 and PyeongChang 2018. *Br J Sports Med* 2021;55(1):46–53.

- [11] Emery CA, van Den Berg C, Richmond SA, et al. Implementing a junior high school-based programme to reduce sports injuries through neuromuscular training (iSPRINT): a cluster randomised controlled trial (RCT). *Br J Sports Med* 2020;54(15):913–9.
- [12] An KO, Lee KJ. Sports injury prevention and functional training: a literature review. *Asian J Kinesiol* 2021;23(1):46–52.
- [13] Salim J, Wadey R. Using gratitude to promote sport injury-related growth. *J Appl Sport Psychol* 2021;33(2):131–50.
- [14] Steffen K, Soligard T, Mountjoy M, et al. How do the new Olympic sports compare with the traditional Olympic sports? Injury and illness at the 2018 Youth Olympic Summer Games in Buenos Aires, Argentina. *Br J Sports Med* 2020;54(3):168–75.
- [15] Lystad RP, Alevras A, Rudy I, et al. Injury incidence, severity, and profile in Olympic combat sports: a comparative analysis of 7712 athlete exposures from three consecutive Olympic games. *Br J Sports Med* 2021;55(19):1077–83.
- [16] Bolling C, Barboza SD, Van Mechelen W, et al. Letting the cat out of the bag: athletes, coaches, and physiotherapists share their perspectives on injury prevention in elite sports. *Br J Sports Med* 2020;54(14):871–7.
- [17] Derman W, Runciman P, Jordaan E, et al. High incidence of injuries at the PyeongChang 2018 paralympic winter games: a prospective cohort study of 6804 athlete days. *Br J Sports Med* 2020;54(1):38–43.
- [18] Fort-Vanmeerhaeghe A, Milà-Villaruel R, Pujol-Marzo M, et al. Higher vertical jumping asymmetries and lower physical performance are indicators of increased injury incidence in youth team-sport athletes. *J Strength Cond Res* 2022;36(8):2204–11.
- [19] Truong LK, Mosewich AD, Holt CJ, et al. Psychological, social, and contextual factors across recovery stages following a sport-related knee injury: a scoping review. *Br J Sports Med* 2020;54(19):1149–56.
- [20] Gabbett TJ. Debunking the myths about training load, injury and performance: empirical evidence, hot topics and recommendations for practitioners. *Br J Sports Med* 2020;54(1):58–66.
- [21] Schmitz D, Ek WE, Berggren E, et al. Genome-wide association study of estradiol levels and the causal effect of estradiol on bone mineral density. *J Clin Endocrinol Metab* 2021;106(11):e4471–86.
- [22] Daminov AT, Xurramova S, Islomov A, et al. Type 2 diabetes and bone mineral density in postmenopausal women. *Sci Educ* 2023;4(11):19–27.
- [23] Fang X, Huang H, Zhang H, et al. High-resolution terahertz ATR frequency-domain spectroscopy for monitoring spinal cord injury in rats. *Biomed Opt Express* 2023;15(1):479–90.
- [24] Rogers NB, Hartline BE, Achor TS, et al. Improving the diagnosis of ipsilateral femoral neck and shaft fractures: a new imaging protocol. *JBJS* 2020;102(4):309–14.
- [25] Jyoti R, Jain T, Damiani M. The expanding role of imaging in the diagnosis and management of sports injuries. *Aust J Gen Pract* 2020;49(1/2):12–5.
- [26] Ehresman J, Pennington Z, Schilling A, et al. Novel MRI-based score for assessment of bone density in operative spine patients. *Spine J* 2020;20(4):556–62.
- [27] Huang W, Gong Z, Wang H, et al. Use of MRI-based vertebral bone quality score (VBQ) of S1 body in bone mineral density assessment for patients with lumbar degenerative diseases. *Eur Spine J* 2023;32(5):1553–60.
- [28] Dagan N, Elnekave E, Barda N, et al. Automated opportunistic osteoporotic fracture risk assessment using computed tomography scans to aid in FRAX underutilization. *Nat Med* 2020;26(1):77–82.
- [29] Greener JG, Kandathil SM, Moffat L, et al. A guide to machine learning for biologists. *Nat Rev Mol Cell Biol* 2022;23(1):40–55.
- [30] Janiesch C, Zschech P, Heinrich K. Machine learning and deep learning. *Electron Mark* 2021;31(3):685–95.
- [31] Al-Garadi MA, Mohamed A, Al-Ali AK, et al. A survey of machine and deep learning methods for internet of things (IoT) security. *IEEE Commun Surv Tutor* 2020;22(3):1646–85.
- [32] Da'u A, Salim N. Recommendation system based on deep learning methods: a systematic review and new directions. *Artif Intell Rev* 2020;53(4):2709–48.
- [33] Sharma K, Giannakos M. Multimodal data capabilities for learning: what can multimodal data tell us about learning? *Br J Educ Technol* 2020;51(5):1450–84.
- [34] Bi X, Hu X, Wu H, et al. Multimodal data analysis of Alzheimer's disease based on clustering an evolutionary random forest. *IEEE J Biomed Health Inf* 2020;24(10):2973–83.
- [35] Ma S, Huang Y, Che X, et al. Faster RCNN-based detection of cervical spinal cord injury and disc degeneration. *J Appl Clin Med Phys* 2020;21(9):235–43.
- [36] Warin K, Limprasert W, Suebnukarn S, et al. Assessment of deep convolutional neural network models for mandibular fracture detection in panoramic radiographs. *Int J Oral Maxillofac Surg* 2022;51(11):1488–94.
- [37] Koch PJ, Park CH, Girard G, et al. The structural connectome and motor recovery after stroke: predicting natural recovery. *Brain* 2021;144(7):2107–19.
- [38] Kato C, Uemura O, Sato Y, et al. Functional outcome prediction after spinal cord injury using ensemble machine learning. *Arch Phys Med Rehabil* 2024;105(1):95–100.