SIN-CHN SCIENTIFIC PRESS PTE.LTD.

Molecular & Cellular Biomechanics 2024, 21(1), 150.
https://doi.org/10.62617/mcb.v21i1.150

Article

Evaluation of the influence of athlete neural activity patterns on the dynamic index of leaping ability using data mining techniques

Lai Liu, Yan Dong*

Sports Teaching Department, Inner Mongolia University of Technology, Hohhot 010000, China
*** Corresponding author:** Yan Dong, 13804745075@139.com

CITATION

Liu L, Dong Y. Evaluation of the influence of athlete neural activity patterns on the dynamic index of leaping ability using data mining techniques. Molecular & Cellular Biomechanics. 2024; 21(1): 150. https://doi.org/10.62617/mcb.v21i1.150

ARTICLE INFO

Received: 20 May 2024
Accepted: 14 June 2024
Available online: 16 October 2024

Abstract: There are many dynamic indicators of jumping ability, and the athlete's neural activity pattern is an important factor in regulating limb activities. This article uses data mining technology to collect, preprocess, data modeling and analysis, and data visualization of dynamic index data of athletes' neural activity patterns of jumping ability. The results show that the jumping ability of athletes with higher neural activity intensity increased significantly after training to around 40 cm–50 cm, while athletes with lower neural activity intensity did not change significantly and remained around 30 cm–35 cm. The overall learning ability of athletes with higher levels of neural activity improved by about 10 cm, and the base of neural activity also increased significantly. It shows that there is a significant correlation between the intensity of neural activity and dynamic indicators of jumping ability, which is the main driving force for athletes' jumping explosive power. The research results can help formulate reasonable and scientific training methods to improve athletes' jumping ability and overall sports level.

Keywords: leaping ability index; neural activity pattern; data mining technology; dynamic index

1. Introduction

The nervous system of athletes can guide the contraction of their muscles, which means that their neural activity has a significant impact on the elasticity of their muscles [1,2]. Scientific training methods for athletes are beneficial for achieving better exercise results, and their neural activity system stores sensory feedback on the intensity of core muscle activity. The leaping ability of athletes is a very important athletic quality and a technical action in sports. The indicators of leaping ability motivation can come from overall strength, reaction speed, body coordination, flexibility, etc. There is an interaction between neural activity patterns and the dynamic indicators of leaping ability. Analyzing the relationship between athletes' neural activity patterns and their leaping ability can provide reliable data basis for athletes' training, thus scientifically conducting training and achieving the best results on the field. In recent years, under the influence of artificial intelligence, neural network and computer vision technology have been developing continuously, and data mining technology has become more intelligent. Data mining technology can more scientifically analyze the relationship between athletes' neural activity patterns and leaping ability dynamic indicators, and is also an important research direction for athlete data collection and analysis.

The impact of athletes' nervous system during exercise is enormous. By analyzing athletes' neural activity patterns, scientific basis can be provided for athlete training. The relationship between athletes' neural activity and leaping ability dynamics has received increasing attention. Turrini and other scholars explored the relationship between neural activity and athletic performance, providing an important reference for later scholars to explore the impact of athletes' neural activity patterns on dynamic indicators of jumping ability [3,4]. Kalkhoven and Watsford investigated the relationship between several measures of lower body stiffness and body performance variables of 22 sub elite male football players, and evaluated the individual muscle stiffness of rectus femoris, biceps femoris muscle and medial gastrocnemius muscle muscles. He also evaluated running acceleration, maximum sprint speed, agility, vertical jumping, and muscle strength [5]. Fink et al. investigated the brain activity of football players when imagining creative actions in real-life football decision-making situations. After presenting a short video clip of a football scene, participants had to imagine themselves as a performer and consider a creative or obvious move. The research results showed that during experiments that required significant action, the activation was stronger compared to experiments that require creative action [6]. Clark et al. observed a significant interaction between professional duration and concussion history in order to better understand the issues of concussion and head impact in former American football players, as well as the relationship between white matter integrity and neural activity. The duration of career and the main position of competition seemed to alter the impact of a history of concussion on white matter structure and neural recruitment. Differences in brain structure and function were observed without clinical injury, indicating that multimodal imaging could provide early warning of traumatic neurodegenerative diseases [7]. Hatfield proposed a theoretical perspective on brain activity. This viewpoint characterized expert cognitive motor performance based on neural and psychomotor efficiency, and discussed the impact of mental stress on brain processes during motor performance. This considered multiple levels of explanation from a comprehensive perspective of human performance, including motor performance psychology, cognitive motor neuroscience, and basic biomechanics, so as to understand the motor characteristics of motion and the effort costs involved [8]. These studies have certain research significance, but most of them are explored from a theoretical perspective.

The intelligent analysis method of data mining technology is a new direction of athlete data analysis. Its analysis results can develop reliable training methods for athletes. Data mining technology is a new hotspot in the research of data analysis methods in kinematics. Bhatia Munish proposed a game theory decision-making model inspired by Internet of Things and fog computing, which was used to provide in-depth analysis of athletes' performance in a time sensitive manner. Specifically, the parameters of sports orientation were obtained using intelligent devices and energy-saving mechanisms. Further classification and analysis were conducted based on quantifiable parameters of executable probability and formal index values. A game theory mathematical model was proposed for effective decision-making services between athletes and monitoring personnel. The proposed model could improve performance in sensitivity (93.14%), specificity (93.97%), and accuracy (94.56%) [9]. Zeng analyzed the current development status of the evaluation system for teaching quality of physical education courses in universities, and analyzed the applicability of data mining technology and hidden Markov models to the evaluation of teaching quality of physical education in universities. He proposed a mathematical model for evaluating the quality of physical education teaching in universities, which helped to improve the accuracy of the evaluation of physical education teaching quality in universities. The research results provided useful exploration for the integration of computing technology and language teaching, and provided reference pathways and implementation models for improving physical education teaching for college graduates through machine learning technology [10]. These literatures have certain reference significance for studying the relationship between the nervous system of athletes and the dynamic indicators of leaping ability, but they have not been analyzed in conjunction with actual situations.

The purpose of this study was to explore the relationship between neural activity intensity and athletes' jumping ability, with a special focus on changes before and after training. Assuming that there is a significant correlation between neural activity intensity and jumping ability, especially after training, athletes with higher neural activity intensity may show greater improvements in jumping ability. The experiment explores this hypothesis through data collection, analysis and visualization of neural activity intensity and jumping ability, and provides more scientific and effective guidance for athletes' training. Dynamic indicators of athletes' jumping ability are greatly affected by their neural activity patterns. Studying the relationship between the nervous system and dynamic indicators of jumping ability is crucial to providing accurate training data. This article introduces data mining methods, uses decision tree algorithms to collect and analyze athletes' neural activity data and jumping ability data, and analyzes the relationship between the two through data visualization.

2. Investigation on the influence of athlete neural activity patterns on leaping ability dynamics

2.1. Leaping ability dynamic indicators

The leaping ability of athletes is achieved by controlling their skeletal muscle groups and utilizing the fast muscle fibers in their skeletal muscles to complete the jumping action. The strength of leaping ability depends on the strength of muscle contraction and the control of motor nerves over skeletal muscles. Motor neurons can simultaneously drive multiple muscle fibers for contraction, and the burst of leaping ability requires strong muscle strength and fast muscle contraction speed. The physical indicators that affect leaping ability come from multiple factors, including takeoff strength muscle group, arm swing strength muscle group, thigh and calf strength muscle group, waist and abdominal strength muscle group, and so on. Strength and endurance are very influential and important factors in winning competitions [11].

Firstly, there is the takeoff strength muscle group. When an athlete jumps, there must be a certain reaction force, which is the vertical force facing the athlete during takeoff, thus acting on each muscle group of the athlete's joints. The takeoff strength is an instantaneous force. The greater the strength of an athlete's takeoff, the greater the impulse that the ground brings to the athlete's body, which is reflected in the height of the jump. The greater the effective impulse of the ground facing athlete, the higher the takeoff height. However, the speed of takeoff is a joint effect of the coordination of various muscle groups in athletes. The arm swinging strength of athletes is crucial, and the upper limb muscle group of athletes is an important force for limb bouncing. The degree of arm swinging strength can increase ground impulse, and it can provide a certain amount of momentum for bouncing during takeoff.

Secondly, the explosive force of athletes' leg muscles is also the main factor affecting leaping ability. The leg muscles include thigh muscles and calf muscles. The greater the strength of leg and calf deltoid muscle muscles, the better the leaping ability. However, the development of leg muscles does not determine the height of leaping ability, and the explosive force of leg strength can affect the athlete's leaping ability. Waist and abdominal strength can drive an athlete's body to complete bouncing movements. Leaping ability may seem to be achieved by athletes using their feet, but it is not. When jumping, the muscles in the waist exert force and drive the body and upper limbs, which can only be applied to the ground to obtain greater ground reaction force. The waist and abdomen muscles can bend and rotate the athlete's body forward and backward, so they play an important role in training the athlete's leaping ability, as shown in **Figure 1**:

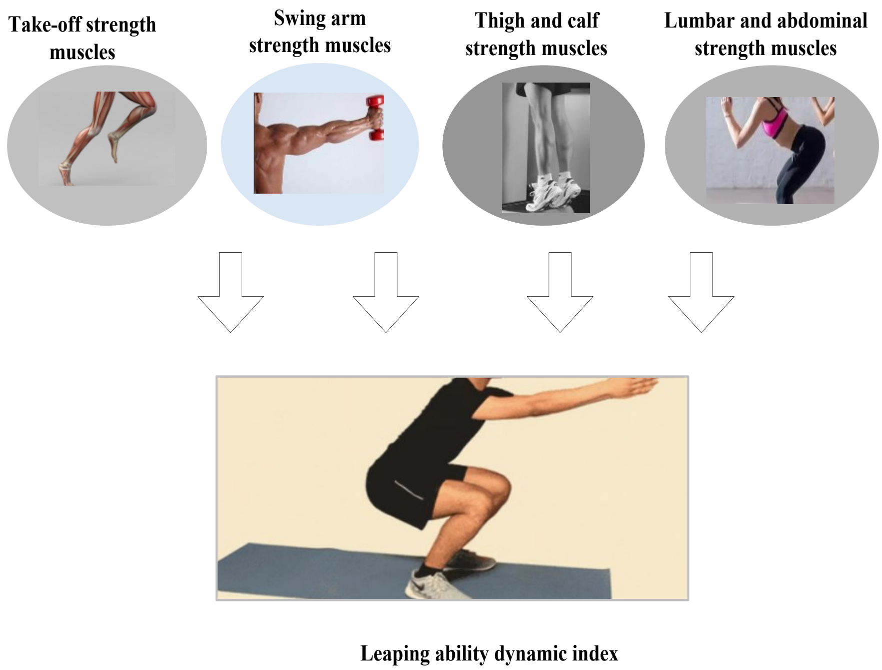


Figure 1. Body muscle group indicators that affect leaping ability.

In addition to muscle strength, physical indicators such as height and weight are also factors that affect leaping ability. Some athletes are not tall, but their leaping ability is very good. This is because although height affects leaping ability, it is not a decisive factor. Strictly speaking, the athlete's standing and touching height have a significant impact on leaping ability. Weight also has an impact on athletes' leaping ability, but it is not a superficial weight. This "weight" refers to the amount of body fat, which is the body fat content and fat content of athletes. Athletes' body fat is generally controlled at a very low level, so their leaping ability is better than that of ordinary people.

The factors that affect the motivation of leaping ability are not only the strength of a certain muscle group, but also the comprehensive strength of the whole body. The influencing factors such as leg muscle groups, arm swing strength, waist strength muscle groups, and takeoff strength described above can only be utilized to achieve the best leaping ability effect for athletes. How to control the various muscle groups of the body so that they can operate in harmony? Leaping ability is the result of a combination of physical qualities such as speed and strength, physical coordination and flexibility, and is an instant explosive effect. By emitting signals from motor neurons, the effect of strong stimulation can stimulate athletes' muscle groups to contract and generate enormous abilities, which can be transformed into stronger motivation.

2.2. Investigation on the relationship between athlete neural activity model and leaping ability dynamic index

2.2.1. Impact of the nervous system on movement

The nervous system of the human body controls the motor function of athletes, and neurons can perceive external signals, process and integrate them, thus conducting a series of cognitive activities such as learning, memory, and thinking. Neuromodulation improves the cognitive function of treatment and motor performance of several nervous system disease [12]. With the continuous improvement of motor function, athletes can complete difficult movements, which are inseparable from the control of the athlete's nervous system. Motor neurons regulate the athlete's limbs and various muscle groups. The complexity of exercise varies depending on the level of conscious control generated by athlete neurons, and can be divided into reflex, random, and rhythmic categories.

Reflex movement refers to a type of movement caused by specific sensory stimuli, which is the simplest form of movement [13,14]. Due to its fixed trajectory, this type of movement is influenced by the size of sensory stimuli and is generally not controlled by consciousness. The duration of reflex movement is also relatively short, because the number of motor neurons is also small. The term "subconscious actions" in everyday life can be expressed as reflex movements of motor neurons. The random movement is more complex than the reflex movement, and is controlled by the athletes' cerebral cortex. The direction and track of this movement can be selected and changed at will, that is, the movement carried out by athletes to achieve a certain purpose. Random movements can be divided into simple and complex types. Complex random movements require multiple exercises to fully master, and some technical movements require learning and repeated contact to complete. Finally, there is rhythmic movement, which is neither reflexive nor arbitrary, and can be said to be in between. This type of movement is not only regular, but can also be autonomously controlled. It can start and stop at will, and can be modulated during movement.

The neural activity pattern plays a decisive role in motor activity [15,16]. Nerves can regulate motor muscle groups, transmit signals to the nervous system or neurons of the human body, thereby causing excitement and regulation, and improving the body function of athletes. The flexibility of neural activity mode refers to the degree to which excitation and inhibition mutually transform, and the flexibility performance determines the efficiency of muscle contraction. It has been said that athletes have a high explosive force when bouncing, indicating that their neural activity mode is also more flexible.

2.2.2. Relationship between neural activity patterns and leaping ability dynamics

The brain nervous activity of athletes regulates physical movement, and leaping ability function is controlled through the central nervous system of the brain. Leaping ability belongs to a type of random motion, which is completed on the basis of reflective motion. Bouncing receives information stored in the athlete's central nervous system. Combined with external signals, after comprehensive analysis of the brain's nerves, and under the control of advanced consciousness, the muscles in the body are stimulated to contract, thus completing the bouncing action.

The nervous system of athletes plays a leading role during exercise, and the nervous system has different neural activity patterns. The central and peripheral nerves work together to connect the various organs and muscle systems of athletes, which is complex. The role of the nervous system in the athlete's body is to maintain internal environmental balance. When the athlete performs bouncing movements, the nervous system maintains a unified balance of the body while also coordinating with the external environment. The various organs, muscle systems, and motor functions of the human body are directly or indirectly regulated and controlled by the nervous system.

The neural activity pattern of athletes refers to the fixed response pattern formed by the nervous system in certain neuronal combinations under external stimuli. Under constant stimulation, the response mode would continuously establish new response modes with the stimulus factors. That is to say, this reaction is a brief process. The nervous system's response mechanism under constant stimulation, and the body would continue to match this mechanism until neurons no longer respond. This model can greatly improve the analytical and reactive abilities of the external environment. Combining this principle with the athlete's leaping ability drive, when the athlete repeatedly attempts to bounce, the body would respond to constant external stimuli and neurons would respond. Under repeated stimuli, the athlete's neural activity patterns would be matched based on each stimulus trace, and the athlete's body would respond differently each time. With the repetition and extension of neural stimulation, each reaction process is brief, and each somatic response would fade with the new response. Therefore, the changes in the neural activity patterns of athletes during each bounce should be analyzed and recorded in detail. It is necessary to analyze this process, and the changes in neural activity patterns during each bounce should be observed. The neural activity patterns and leaping ability data of athletes need to be collected, and the relationship between the two needs to be analyzed. How to intuitively present the complex relationship between neural activity and leaping ability dynamics indicators to facilitate data analysis and discussion? Conventional analysis methods can provide general analysis of exercise training indices, but their ability to analyze niche data is relatively low [17]. This article would introduce data mining techniques for collecting and analyzing athlete neural activity and leaping ability data.

2.3. Data mining techniques for collecting and evaluating athlete data

Adaptive control is a control method that can automatically adjust control parameters to adapt to system changes. During athlete training, the athlete's physiological state and performance will change with time and training. The use of adaptive control methods in research can make the training process more flexible and efficient. In jump training, the training parameters can be automatically adjusted according to the intensity of the athlete's neural activity and performance to achieve the best training effect.

Based on the cooperative fault-tolerant adjustment output of the adaptive dynamic event trigger mechanism, it realizes cooperative control in the multi-agent system and has fault tolerance. Even if some agents in the system fail or are abnormal, the system can still maintain normal operation. In athlete training, athletes can be regarded as agents, and the method of cooperative fault-tolerant adjustment output is used to realize cooperative motion control in team training or competition to ensure the optimal training effect of the entire team.

Dynamic event-triggered fixed-time tracking control of nonlinear systems with dead-zone state constraints based on fast fixed-time filters is mainly used in the control of nonlinear systems and has the characteristics of fast response and fixed-time convergence. In athlete training, the athlete's physical state and sports performance are regarded as nonlinear systems, and the dynamic event-triggered fixed-time tracking control method is used to adjust the training parameters in the training process to ensure that the athlete's training effect reaches the expected goal.

Methods such as adaptive control provide important ideas and methods for solving challenges and problems in athlete training. Data mining technology is now introduced to collect and evaluate athlete data.

Data mining is not just the process of obtaining data. Data mining includes data collection, data sorting, data visualization, data analysis, etc. Data mining technology refers to the process of extracting valuable information from a large amount of data and conducting inductive reasoning. Data mining can be used in any situation where a large amount of data needs to be examined, and all data mining tools, including analysis, can be considered as part of the data mining process [18]. The role of data mining is to highly automate the analysis of target data, and make induction and inference, so as to discover potential patterns and help people adjust strategies and make correct decisions. For athletes' data mining, data mining technology can integrate the data of athletes' neural activity data and leaping ability data, and summarize them, so as to infer the logical relationship between them and analyze them for athletes' reference. It can accurately analyze the relationship between neural activity patterns and leaping ability dynamic indicators, thus making scientific training methods and maximizing exercise potential. Identifying the biological characteristics of athletes makes a significant contribution to the classification of their specific skills [19].

The first step of data mining technology is to collect data. When athletes perform bouncing movements, data on their physical fitness indicators, as well as data on their muscle contractions, as well as the height of the jump, must be recorded. Recording the dynamic index data of leaping ability can be collected using force monitoring equipment. At the same time, when athletes perform jumps, neural monitoring instruments are used to monitor the changes in their neural activity and record the changes in neural activity for each jump. Using high-quality instruments during data collection can improve the quality of data analysis. After data collection, data preprocessing is carried out, which involves processing the raw data of athlete neural activity and leaping ability dynamics indicators collected [20]. The data is analyzed and modeled. Data analysis and modeling are important steps in data mining [21]. Data analysis can be considered an iterative process of discovering insights from data to make better and faster decisions. The methods of data analysis and modeling can be combined with those in machine learning. The analysis of athletes' physiological signals is a challenging task that requires the use of specific methods, such as knowledge discovery in database processes. Due to the fact that athletes' neural activity data and leaping ability dynamic index data may come from multiple aspects and dimensions, analysis should be combined with athletes' physical indicators, such as height, weight, and other sample data characteristics. In this paper, machine learning method was used for data modeling and analysis.

Decision trees are a typical classification method in machine learning. Machine learning technology is a powerful tool used in various aspects of science, and their applications in sports are relatively novel [22–24]. The principle is to preprocess the data, use induction algorithms to generate readable rules and decision trees, and then use decision trees to analyze the new data. Decision tree algorithms can be used in different fields, which can be used to search for data and extract text in alternative statistical programs. They can also be used in medical authentication fields and search engines [25–27]. Typical algorithms for decision trees include ID3 (Iterative Dichotomiser 3), C4.5, CART (Classification and Regression Tree), and so on. The ID3 algorithm is one of the more typical and fundamental algorithms [28]. The principle is to do more with less, including information entropy, conditional entropy and information gain. Its core idea is to use information gain to measure the selection of attributes and split the attribute with the largest information gain after splitting. information entropy represents a random variable. The greater the entropy, the greater the uncertainty of the variable, which can be defined as the following equation:

$$\mathrm{F(x)} = -\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{LOG_2 p_i} \tag{1}$$

In Equation (1), *p* represents the probability distribution of the random variable *x*. The conditional entropy of the ID3 algorithm represents the uncertainty of random variable *y* under the condition of known random variable *x*, which can be expressed by the following equation:

$$\mathrm{F(y|x)} = \sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{p_i\ F(y|x = x_i), p_i = p(x = x_i)} \tag{2}$$

In Equation (2), $\mathrm{F(y|x)}$ represents the uncertainty of random variable *y* under the condition of known random variable *x*. Finally, there is information gain, which represents the difference between empirical entropy and empirical conditions. The equation is as follows:

$$\mathrm{G(M, N) = F(M) - G(M|N)} \tag{3}$$

In Equation (3), $\mathrm{F(M)}$ represents empirical entropy, and $\mathrm{G(M|N)}$ represents empirical conditional entropy. Using decision tree models to model data can improve the efficiency of data analysis and enhance its automated data analysis effectiveness.

After data analysis and modeling, data visualization is finally carried out, which is to visualize the analysis results of athletes' neural activity mode data and leaping ability dynamics data, and present the relationship between them in the form of charts for convenient observation and discussion. The following is a simulation analysis experiment.

Decision tree is a machine learning algorithm for classification and regression. It generates a tree model by gradually dividing the data to predict the value of the target variable. The decision tree algorithm is used to analyze the relationship between the intensity of neural activity and jumping ability. The decision tree algorithm selects the training set data for modeling, selects the feature with the largest information gain for node division, and recursively divides the data set to build a decision tree model until the stopping condition is met to complete the analysis of the collected data.

3. Simulation experiment on highly correlated data between athletes' neural activity intensity and leaping ability

3.1. Data collection and preprocessing

This simulation experiment selected 200 athletes from a certain school's sports team. Firstly, by testing the intensity data of the neural activity of the 200 athletes, that is, their flexibility, a neural monitoring instrument was used to conduct a data experiment on the intensity of neural activity. Each team underwent a 5-minute neural activity intensity experiment for each remote mobilization. When the neural activity intensity reached a value of 2250, it was indicated as a group with strong neural activity flexibility. When the neural activity intensity did not reach a value of 2250, it was indicated as a group with poor neural activity flexibility. These two sets of data could be divided into four levels based on their numerical value: very strong, strong, average, and weak.

In this experiment, the standard of 2250 values was set. 2250 values are a threshold used in this study to distinguish the intensity of athletes' neural activity, and are used to divide athletes into a group with strong neural activity flexibility and a group with poor neural activity flexibility. The reasons for setting this standard are as follows.

(1) In the preliminary experiment, the study conducted a preliminary analysis of the neural activity data of a large number of athletes and found that the value of 2250 has a good effect in distinguishing the intensity of neural activity.

(2) The value of 2250 can better reflect the activity of the athlete's nervous system. Athletes above this value have a more active and sensitive nervous system.

In order to verify and explore the relationship between neural activity intensity and jumping ability, the experimental procedure is designed as follows:

(1) Experimental subjects

200 athletes from a school sports team were selected as research subjects, and the basic information of each athlete, including height, weight and grade, was recorded.

(2) Data collection

The experiment used a neural monitor to test the athletes' neural activity intensity, and each test lasted for 5 minutes. The athletes' neural activity intensity data were recorded, and the athletes were divided into two groups according to the value of 2250: a group with strong neural activity flexibility and a group with poor neural activity flexibility.

(3) Data modeling

The decision tree algorithm was used to establish a model between neural activity intensity and jumping ability, and the correlation was analyzed. The study identified the neural activity features that had the greatest impact on jumping ability by ranking the features by importance.

(4) Jumping ability test

The experiment conducted a standing jump height test on all athletes and recorded the jumping height data of each athlete. Each athlete performed 20 jump tests and recorded the jumping height of each time.

(5) Training intervention

The experiment conducted professional jumping training for all athletes for several weeks. The training content included strength training, coordination training and explosive power training. Ensure that the training content and intensity were consistent to facilitate the comparison of data changes before and after training.

(6) Post-training test

The athletes were tested for neural activity intensity and the neural activity intensity data after training were recorded. The jumping ability test was performed again and the jumping height data after training was recorded.

(7) Data analysis

Data mining technology was used to analyze the collected data using a decision tree algorithm to explore the correlation between neural activity intensity and jumping ability.

After data collection, this paper preprocesses the data.

(1) Data screening

The experiment uses the statistical method 3σ principle to identify and process outliers, and chooses to use interpolation to fill missing values and outliers.

(2) Data classification

This paper uses thresholds to divide the intensity of neural activity into four levels: “very strong”, “strong”, “average” and “weak”.

(3) Data conversion

For the continuous intensity of neural activity, it is converted into discrete data, divided into different intervals, and the Z-score standardization method is used to convert the data into a distribution with a mean of 0 and a standard deviation of 1.

In this experiment, the tools and instruments used to measure neural activity are mainly high-precision neural monitors (EEG electroencephalograms). During the measurement process, each athlete is first asked to wear an EEG helmet in a quiet and relaxed state. Each experiment lasts for 5 minutes, and the neural activity data during this period are recorded.

For the collected EEG data, the following specific indicators are extracted to quantify the intensity of neural activity.

α wave: related to the state of relaxation. β wave: related to active thinking and concentration. θ wave and δ wave: related to deep relaxation and sleep state.

In the study, the quantification method is to use the average amplitude value of β wave as the quantification standard of neural activity intensity. When the average amplitude value reaches or exceeds 2250 μV, it is classified as a group with strong neural activity flexibility; when it is lower than 2250 μV, it is classified as a group with poor neural activity flexibility.

The tools and instruments used to measure jumping ability use a high-precision force platform and motion capture system (Vicon system). The quantitative indicator is the jump height (in cm), and the maximum height of each jump is recorded. During the measurement process.

(1) First, let each athlete stand on the force platform, jump as hard as possible from a static state, and record their jump height.

(2) Each athlete performs 20 jump tests and records the take-off height each time.

(3) Use a motion capture system to accurately record the athlete’s take-off process and height.

The following are the results of the test:

Table 1. Numerical testing of athletes’ neural activity intensity.

Athlete number	Height(cm)	weight(kg)	Intensity of neural activity	Grade
1	175	61	2190	Average
2	187	77	2241	Average
3	181	73	2263	Strong
4	178	75	2319	Very strong
5	169	66	2260	Strong
6	170	70	2014	Weak
7	188	78	2289	Strong
8	183	77	2477	Very strong
9	184	74	1980	Weak
10	191	80	2291	Strong
...	...	...	...	...
200	186	74	2055	Weak

Table 1 tested the numerical values of height, weight, and neural activity intensity (flexibility) of 200 athletes, and then classified them into four different types of neural activity athletes based on the values. The table showed that the neural activity intensity varied for different heights and weights, but specific changes could not be seen yet. Due to limited conditions, the display of some athlete data was omitted in the middle.

3.2. Jumping ability height of athletes with different neural activity intensities before and after training

After collecting data on the intensity of neural activity, the leaping ability of 200 athletes was tested. The explosive power of the test athlete’s leaping ability was based on the actual height of the jump in place as the numerical basis for explosive power. The explosive power of leaping ability was controlled through the athlete’s central nervous system, and muscle contraction was related to the intensity of nerve stimulation. **Figure 2** shows the data of athletes’ leaping ability height before training according to the numerical test in **Table 1**:

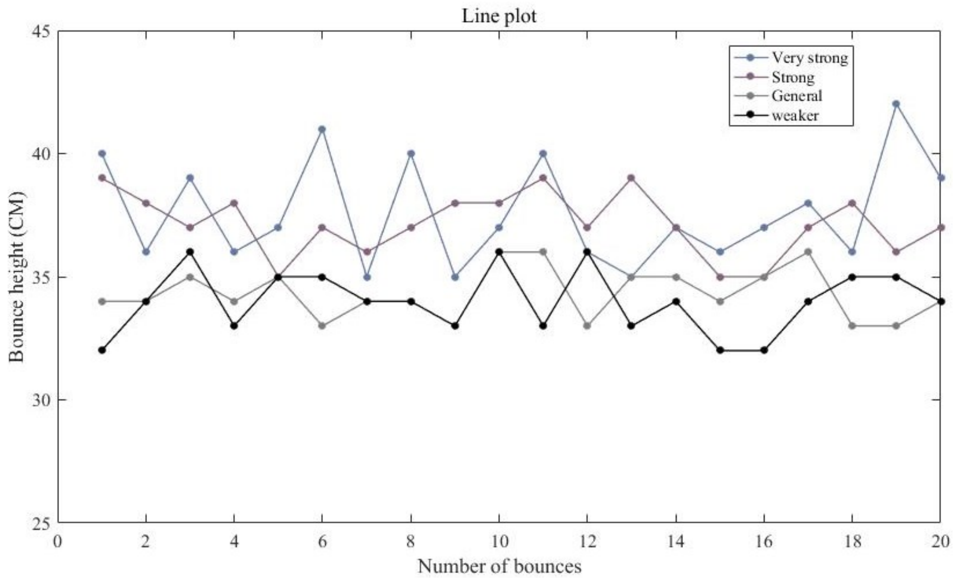


Figure 2. Leaping ability height of athletes with different neural activity intensities before training.

Figure 2 shows the jumping height of athletes with different neural activity intensities before retraining. The line chart in the figure showed that 50 athletes performed 20 bouncing movements respectively, and then divided them according to the intensity level of neural activity. From the numerical values in the figure, it could be seen that athletes with very strong and strong levels of neural activity had slightly higher levels of leaping ability compared to athletes with average and weak levels of neural activity, but the difference was not significant. The data showed that in the height of athletes' leaping ability before training, athletes with stronger neural activity (flexibility) had a leaping ability height of around 35 cm–45 cm, while athletes in the poorer group had a leaping ability height of around 30 cm–35 cm. Although the height difference in leaping ability between the two groups of athletes was not significant, athletes with higher values of neural activity intensity performed slightly better in leaping ability. After conducting professional training on the leaping ability of 50-meter athletes, the data values of the athletes' jumping height after training were obtained, as shown in **Figure 3**.

Figure 3 shows the height of leaping ability tested after jumping training on 200 athletes. The data in the figure shows that athletes with different levels of neural activity have significantly greater differences in jumping heights compared to pre training jumping heights. After training, the leaping ability of the group with strong neural activity intensity significantly improved, which was about 10 cm higher than before the training. The height of leaping ability increased to around 40 cm–50 cm. However, there was no significant change in the height of leaping ability in the group with poor neural activity intensity, which was still around 30 cm–35 cm. This indicated that training improved the explosive power of leaping ability. At the same time, the intensity of neural activity, also known as flexibility, played a significant advantage in the burst of leaping ability. After training, the athlete's nerves were stimulated, thus reflecting the comprehensive muscle group of the body, which directly affected the speed and strength of the leaping ability. Therefore, it could be seen that the flexibility of neural activity patterns could determine the efficiency of muscle contraction, thereby improving the height of bounce.

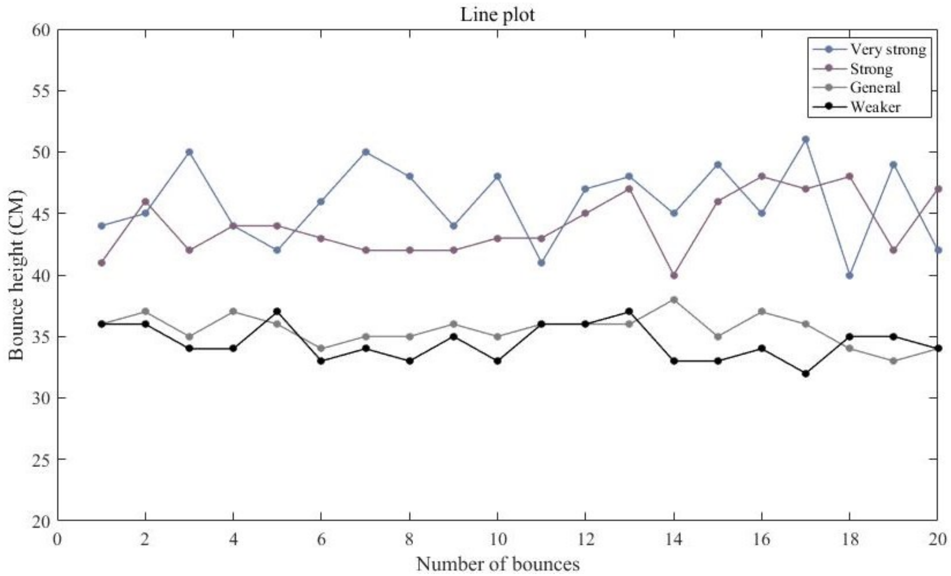
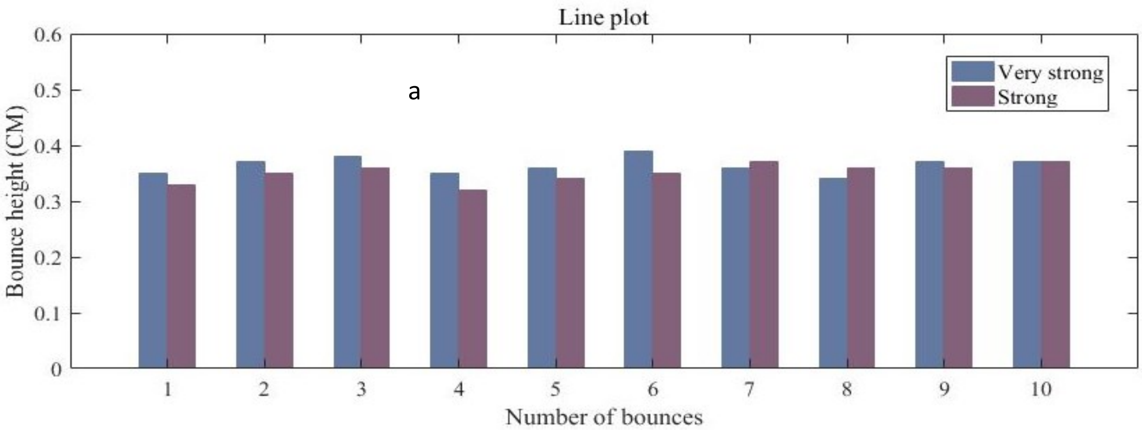


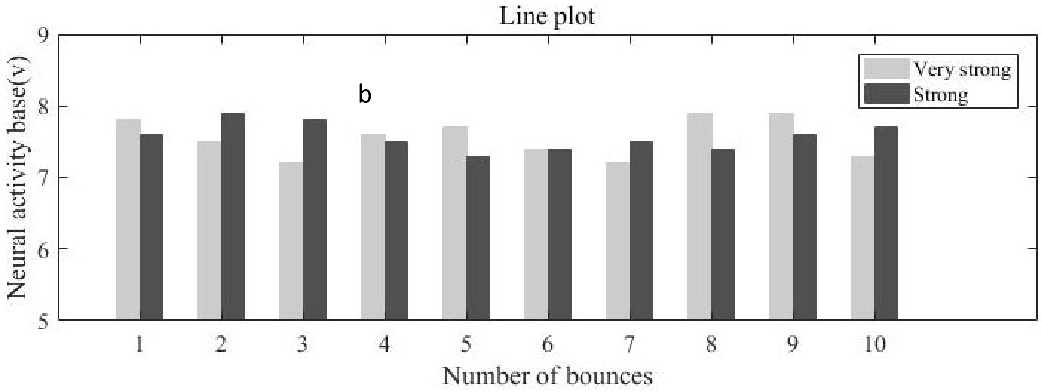
Figure 3. Leaping ability height of athletes with different neural activity intensities after training.

3.3. Jumping ability test results of athletes with "very strong" and "strong" neural activity intensity before and after training

The following tests would be conducted on the leaping ability of two types of athletes with "very strong" and "strong" neural activity intensity, as shown in **Figure 4**:



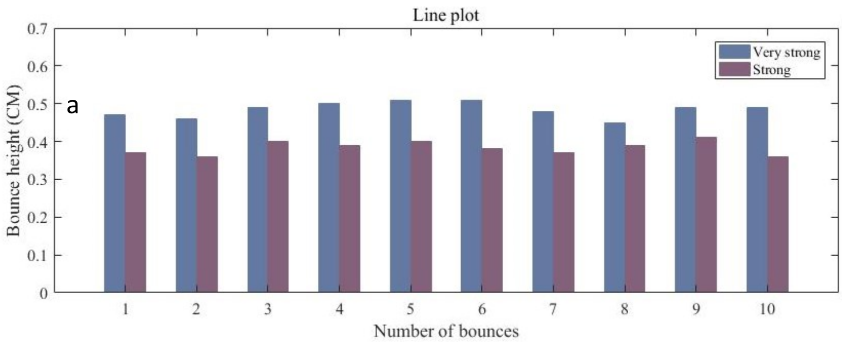
(a)



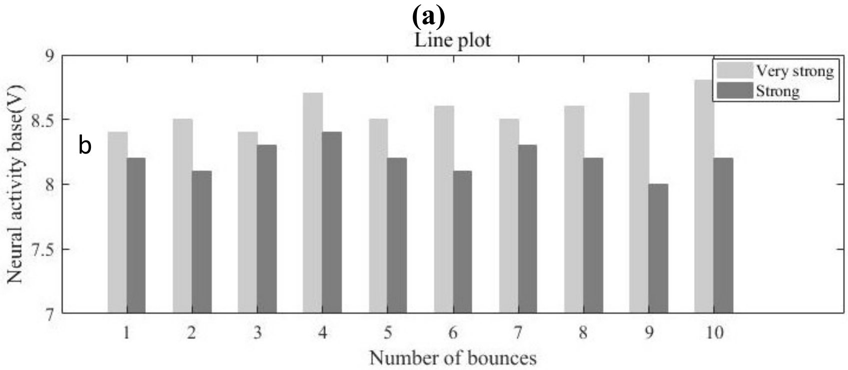
(b)

Figure 4. Data on athletes with "very strong" and "strong" neural activity intensity before training: **(a)** athlete jump height; **(b)** changes in the cardinal activity of athletes.

Figure 4 shows the changing values of the leaping ability and neural activity base of athletes with "very strong" and "strong" levels of neural activity intensity tested. **Figure 4a** shows the jumping height of 10 athletes tested. Before training, both the "very strong" level of neural activity intensity and the "strong" level of neural activity athletes had a jumping height of about 0.35 meters. The average bounce height of athletes in the "very strong" level was higher. Looking at **Figure 4b** again, it shows the changes in the neural activity base of athletes during each bounce. From the data in the figure, it could be seen that the values of each bounce changed. Next, these two groups of athletes were trained, and the values of the jump height and neural activity base changes after training were shown in **Figure 5**:



(a)



(b)

Figure 5. Data on athletes with "very strong" and "strong" neural activity intensity after training: **(a)** Athlete jump height; **(b)** Changes in the cardinal activity of athletes.

From the data in **Figure 5**, it can be seen that there has been a significant change in the neural activity base of athletes after training. For athletes with a "very strong" level before training, the height of their leaping ability and neural activity base were significantly higher than those with a "strong" level. **Figure 5a** shows that after training, athletes with higher levels of neural activity overall improved their leaping ability by about 10 cm. The data in **Figure 5b** shows that the neural activity base has also increased to over 8 V. Athletes with a "strong" level of neural activity intensity also showed an increase in leaping ability height and neural activity base. However, the increased base is not as high as athletes in the "very strong" level. Therefore, it can be concluded that an increase in the flexibility of the athlete's nervous system before and after training can lead to an increase in the height of jumping, and it also proves that there is a certain relationship between the intensity of neural activity and the explosive leaping ability of the athlete.

3.4. *T*-test analysis of the correlation between neural activity intensity and jumping ability after training

Experimental statistical steps:

(1) Use *T* test to compare the jumping ability of different neural activity intensity groups before and after training, and calculate the average jumping ability, standard deviation and confidence interval of each group of samples.

(2) Conduct hypothesis testing to verify the correlation between neural activity intensity and jumping ability after training.

(3) Calculate the p value and judge the significance of the research results.

The T test results are shown in **Table 2**.

Table 2. *T* test results.

Neural activity intensity level	Average jump height before training (cm)	Average jump height after training (cm)	Standard deviation before training	Standard deviation after training	Confidence interval (95%)
very strong	42.5	52.3	2.1	3.5	(48.6, 56.0)
strong	39.8	48.9	2.5	3.2	(45.1, 52.7)
average	36.2	45.7	2.9	3.6	(41.9, 49.5)
weak	33.5	40.2	3.2	4	(37.1, 43.3)

In **Table 2**, it can be seen that the p value is 0.001 (significance level $\alpha = 0.05$), indicating that there is a significant difference in the jumping ability of different neural activity intensity groups before and after training. It can be seen that the neural activity intensity and the jumping ability after training are significantly different. Correlation.

4. Experimental discussion

This article examines the implications of the results for athletic training and performance.

(1) In terms of guidance on training methods, research results show that there is a significant correlation between the intensity of neural activity and jumping ability, especially in terms of post-training effects. This provides important information for formulating reasonable and scientific training methods for athletes' basis. Training

programs can be tailored to individual neural activity levels to improve jumping ability and athletic performance.

(2) In terms of strengthening personalized training, understanding athletes' neural activity patterns can help coaches better develop personalized training plans. Athletes of different levels require different types and intensities of training to achieve optimal athletic performance.

(3) In terms of optimizing training effects, experiments can optimize training effects and improve athletes' performance levels by studying the relationship between neural activity patterns and jumping ability. For athletes with weak neural activity, relevant training can be strengthened to improve their jumping ability and overall sports level.

(4) At the athletes' cognitive level, athletes' awareness of their own neural activity patterns and jumping abilities can help them better understand their strengths and weaknesses, and thus conduct more targeted training and adjustments.

This article has made some achievements, but there are also potential limitations. There are limitations in sample selection and research design. The sample of this study comes from a sports team of a certain school and cannot represent all types and levels of athletes. And the study results were affected by factors such as diet and sleep that were not taken into account.

Future research will consider expanding the sample to include athletes of different ages, genders, and sports, as well as considering in more detail other factors that may influence jumping ability. Further explore the relationship between neural activity patterns and other sports ability indicators, such as speed, strength, etc., to fully understand the impact of neural activity on sports performance. Research uses more complex data analysis methods and machine learning algorithms to mine deeper patterns and associations in the data.

5. Conclusions

The scientific training methods mastered by athletes during training, as well as the training data generated during training, are extremely important for training effectiveness. Recording and analyzing these data is a very important step in the training process. The influencing factors of leaping ability dynamics are from various muscle systems of the body, and these muscle systems are controlled by the central nervous system. Analyzing the relationship between athletes' neural activity patterns and leaping ability motivation plays an important role in promoting athletes' training. This article explored the dynamic indicators of leaping ability, and analyzed multiple influencing factors, the role of the nervous system in athlete muscles, and the relationship between neural activity patterns and athlete leaping ability. Data mining techniques were used to collect and analyze the neural activity intensity data and leaping ability data of athletes, and the visualized data was analyzed. The results further indicated that the neural activity patterns of athletes played an extremely important role in the explosive force of jumping, and also proved the main reason for the differences in muscle strength between individuals. Although there were congenital differences in the patterns of neural activity, it could also be improved through acquired training. By using data mining techniques to analyze the correlation between neural activity patterns and dynamic indicators of athletes' leaping ability, it was possible to timely grasp the physical functional level and potential strength of athletes, and improve training effectiveness.

Author contributions: Conceptualization, LL; methodology, LL; software, LL; formal analysis, LL; writing—original draft preparation, LL and YD; writing—review and editing, LL and YD; visualization, YD. All authors have read and agreed to the published version of the manuscript.

Availability of data and materials: The data and materials of this study are available from the corresponding author.

Ethical approval: Not applicable.

Conflict of interest: The authors declare no conflict of interest.

References

1. Maciejewska-Skrendo A, Leznicka K, Leonska-Duniec A, et al. Genetics of muscle stiffness, muscle elasticity and explosive strength. Journal of human kinetics. 2020; 74(1): 143–159. doi: 10.2478/hukin-2020-0027
2. Kamandulis S, Janusevicius D, Snieckus A, et al. High-velocity elastic-band training improves hamstring muscle activation and strength in basketball players. The Journal of sports medicine and physical fitness. 2020; 60(3): 380–387. doi: 10.23736/s0022-4707.19.10244-7
3. Turrini S, Bevacqua N, Cataneo A, et al. Neurophysiological markers of premotor–motor network plasticity predict motor performance in young and older adults. Biomedicines, 2023, 11(5): 1464–1477. doi: 10.3390/biomedicines11051464
4. Nash D, Hughes M G, Butcher L, et al. IL-6 signaling in acute exercise and chronic training: Potential consequences for health and athletic performance. Scandinavian Journal of Medicine & Science in Sports. 2023; 33(1): 4–19. doi: 10.1111/sms.14241
5. Kalkhoven JT, Watsford ML. The relationship between mechanical stiffness and athletic performance markers in sub-elite footballers. Journal of Sports Sciences. 2018; 36(9): 1022–1029. doi: 10.1080/02640414.2017.1349921
6. Fink A, Bay JU, Koschutnig K, et al. Brain and soccer: Functional patterns of brain activity during the generation of creative moves in real soccer decision-making situations. Human brain mapping. 2019; 40(3): 755–764. doi: 10.1002/hbm.24408
7. Clark MD, Varangis EML, Champagne AA, et al. Effects of career duration, concussion history, and playing position on white matter microstructure and functional neural recruitment in former college and professional football athletes. Radiology. 2018; 286(3): 967–977. doi: 10.1148/radiol.2017170539
8. Hatfield, Bradley D. Brain dynamics and motor behavior: A case for efficiency and refinement for superior performance. Kinesiology Review. 2018; 7(1): 42–50. doi: 10.1123/kr.2017-0056
9. Bhatia M. IoT-inspired framework for athlete performance assessment in smart sport industry. IEEE Internet of Things Journal. 2020; 8(12): 9523–9530. doi: 10.1109/JIOT.2020.3012440
10. Zeng Y. Evaluation of physical education teaching quality in colleges based on the hybrid technology of data mining and hidden markov model. International Journal of Emerging Technologies in Learning (iJET). 2020; 15(1): 4–15. doi: 10.3991/ijet.v15i01.12533
11. Nasuka N, Setiowati A, Indrawati F. Power, strength and endurance of volleyball athlete among different competition levels. Utopia y Praxis Latinoamericana. 2020; 25(10): 15–23. doi: 10.5281/zenodo.4155054
12. Morya E, Monte-Silva K, Bikson M, et al. Beyond the target area: an integrative view of tDCS-induced motor cortex modulation in patients and athletes. Journal of neuroengineering and rehabilitation. 2019; 16(1): 1–29. doi: 10.1186/s12984-019-0581-1
13. Solopova IA, Selionov VA, Blinov EO, et al. Higher responsiveness of pattern generation circuitry to sensory stimulation in healthy humans is associated with a larger hoffmann reflex. Biology. 2022; 11(5): 707–724. doi: 10.3390/biology11050707
14. Pecuch A, Gieysztor E, Telenga M, et al. Primitive reflex activity in relation to the sensory profile in healthy preschool children. International journal of environmental research and public health. 2020; 17(21): 8210–8225. doi:

10.3390/ijerph17218210
15. Dhawale AK, Wolff SBE, Ko R, et al. The basal ganglia control the detailed kinematics of learned motor skills. Nature neuroscience. 2021; 24(9): 1256–1269. doi: 10.1038/s41593-021-00889-3
16. Chen S, Liu Y, Wang ZA, et al. Brain-wide neural activity underlying memory-guided movement. Cell. 2024; 187(3): 676–691. doi: 10.1016/j.cell.2023.12.035
17. Qian L, Liu J. Application of data mining technology and wireless network sensing technology in sports training index analysis. EURASIP Journal on Wireless Communications and Networking. 2020; 121(2020): 1–17. doi: 10.1186/s13638-020-01735-z
18. Sohail M, Talha M, Ikram P, et al. Application of Data Mining Technology in exploring the relationship between cultural sports psychology and intersecting identities. Revista de Psicologia del Deporte (Journal of Sport Psychology). 2021; 30(4): 11–19. Retrieved from https://mail.rpd-online.com/index.php/rpd/article/view/586
19. Khromov N, Korotin A, Lange A, et al. Esports athletes and players: A comparative study. IEEE Pervasive Computing. 2019; 18(3): 31–39. doi: 10.1109/MPRV.2019.2926247
20. Houtmeyers KC, Jaspers A, Figueiredo P. Managing the training process in elite sports: from descriptive to prescriptive data analytics. International Journal of Sports Physiology and Performance. 2021; 16(11): 1719–1723. doi: 10.1123/ijspp.2020-0958
21. Aljawarneh S, Anguera A, Atwood JW, et al. Particularities of data mining in medicine: lessons learned from patient medical time series data analysis. EURASIP Journal on Wireless Communications and Networking. 2019; 260(2019): 1–29. doi: 10.1186/s13638-019-1582-2
22. YILDIZ BF. Applying decision tree techniques to classify European Football Teams. Journal of Soft Computing and Artificial Intelligence. 2021; 1(2): 86–91.
23. Husnain A, Hussain HK, Shahroz HM, et al. Advancements in Health through Artificial Intelligence and Machine Learning: A Focus on Brain Health. Revista Espanola de Documentacion Cientifica. 2024; 18(01): 100–123.
24. Rani P, Kumar R, Jain A, et al. Taxonomy of machine learning algorithms and its applications. Journal of Computational and Theoretical Nanoscience. 2020; 17(6): 2508–2513. doi: 10.1166/jctn.2020.8922
25. Patel HH, Prajapati P. Study and analysis of decision tree-based classification algorithms. International Journal of Computer Sciences and Engineering. 2018; 6(10): 74–78. doi: 10.26438/ijcse/v6i10.7478
26. Jayanthi E, Ramesh T, Kharat RS. Cybersecurity enhancement to detect credit card frauds in health care using new machine learning strategies. Soft Computing. 2023; 27(11): 7555–7565. doi: 10.1007/s00500-023-07954-y
27. Hong S, Walton B, Kim HW, et al. Predicting the behavioral health needs of Asian Americans in public mental health treatment: a classification tree approach. Administration and Policy in Mental Health and Mental Health Services Research. 2023; 50(4): 630–643. doi: 10.1007/s10488-023-01266-x
28. Ju L, Huang L, Tsai SB. Online data migration model and ID3 algorithm in sports competition action data mining application. Wireless Communications and Mobile Computing. 2021; 1(2021): 1–11. doi: 10.1155/2021/7443676