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ORIGINAL

CONSTRUCTION OF ATHLETES' POSITIVE PSYCHOLOGICAL FITNESS ASSESSMENT MODEL BASED ON FUZZY CLUSTERING ALGORITHM AND SECURE NEURAL NETWORK DRIVEN

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ABSTRACT

The social environment faced by athletes is constantly changing, and there are various ways for them to contact. Compared with before, today's athletes are more precocious and sensitive to many things in society. The social environment they are faced with is constantly changing, and their ways of contact are various. In order to improve the accuracy of athletes' positive psychological fitness assessment, this paper analyzes and studies athletes' positive psychological fitness based on system engineering method and DM method, and constructs a positive psychological fitness assessment model based on Fuzzy C-clustering (FCM) and Secure Neural Network as examples. The findings indicate that, following numerous iterations, this method outperforms the comparison algorithm in psychological crisis analysis. The error rate has been substantially reduced by 38.55%, while the recall rate has reached an impressive 96.87%, surpassing the comparison algorithm by 16.04%. These results demonstrate the model's capacity for self-learning, enabling online self-diagnosis of athletes' positive psychological disorders. Moreover, it provides valuable support to psychological counseling and the psychological fitness teams in universities. Given the widespread application of big data in the field of psychological fitness, utilizing big data for studying new approaches to pre-alarm psychological fitness crises has emerged as an

important research direction.

KEYWORDS: Fuzzy clustering; Neural network; Positive Psychological Fitness

1. INTRODUCTION

With the increase of the quantity of athletes and the surge of social problems such as graduation, employment and family conflicts, the psychological fitness problems of athletes have gradually become prominent (Goodwill, Watkins, Johnson, & Allen, 2018). When athletes can't solve the psychological pressure, they are prone to psychological problems, and the psychological fitness of athletes is widely concerned (Dirmaier, Liebherz, Saenger, Haerter, & Tlach, 2016; Ruggiero et al., 2020). Compared with before, today's athletes are more precocious and sensitive to many things in society. The social environment they are faced with is constantly changing, and their ways of contact are various (Barr, Moffatt, & Richiardi, 2022). For individuals, psychological fitness problems will have some negative effects on individuals, worsen their adaptability in society, and even pose a serious threat to their physical health. For psychological fitness workers, the application of big data can improve work efficiency, as well as the personalization and diversification of data. Many surveyed athletes usually express unconsciously, which makes the data information more objective and accurate, and can reflect the psychological development and activities of contemporary athletes.

At present, most universities only rely on the intuitive reflection of the compulsory health test system to understand athletes' psychological state, and compulsory tutors only add, delete and check data when using the psychological health test system (Lees, 2015; Sockalingam et al., 2021). Such test results are subjective to some extent, and can't fully and truly reflect the psychological fitness status of athletes, and at the same time, they can't take the initiative to further prevent and intervene athletes' mental problems (Gracie, Hamlin, & Ford, 2018; Rohrbasser, Wong, Mickan, & Harris, 2022). Taking common psychological fitness assessment models of athletes as an example, this paper constructs a psychological fitness assessment model based on FCM and neural network. With the continuous growth of society, athletes' psychological problems are increasing, and the trend of athletes' psychological fitness problems is becoming more and more prominent. Many research reports point out that the proportion of athletes with problems is very high, which is manifested in compulsion, anxiety, depression, interpersonal sensitivity and lack of self-confidence. Psychological fitness problems have serious harm (Wilson et al., 2022).

Applying the anomaly detection and correlation analysis technology in FCM to the research of athletes' psychological fitness problems, we can discover hidden rules from a large quantity of data of psychological fitness

problems, find out the main factors leading to mental illness, and identify potential mental illness patients in advance. Research on psychological problems through big data has great advantages, which can combine and compare individuals and groups, and study the psychological growth of individuals more comprehensively and truly.

2. Related Work

It is a very meaningful problem to find out the related factors that affect athletes' psychological fitness problems. Bleton et al. proposed using big data to warn psychological crisis and loneliness coefficient, which can reflect athletes' psychological fitness level on a certain level (Lemey et al., 2016). In the aspect of psychological big data analysis, DM and feature extraction algorithm of association rules have played a certain role, but for complex external environmental factors, there are still some deficiencies in how to determine the main factors (Knauer et al., 2022). In their research, Ripp et al. (Hsu, Lu, & Liang, 2020; Ripp, Peccoralo, & Charney, 2020) explored the application of decision-making (DM) tools in medical care, specifically utilizing psychological fitness and breast cancer data sets to evaluate the effectiveness of DM tools in this domain. Terry et al. (Joyce et al., 2012) developed a psychological fitness assessment model using the decision tree C4.5 algorithm. They constructed a decision tree and utilized rule extraction to predict psychological fitness. Dalgleish (Galante, Friedrich, Dalgleish, White, & Jones, 2022) emphasized the significance of understanding athletes' campus life, as it can greatly impact their academic achievements and future career paths. The author suggested exploring this topic, particularly by leveraging big data collected through campus information systems. Henderson et al. (Henderson, Hawke, & Chaim, 2018) proposed a data-driven framework based on athletes' behavior in school to predict their career choices after graduation. Morrissette et al. (Morrissette & Doty‐Sweetnam, 2010) introduced a novel method for detecting depression by analyzing network behavior through time-frequency analysis. Their data sources included athletes' smart card data, internet data, and on-campus behavioral tracking. Phd et al. (Baughman, Tossone, Singer, & Flannery, 2019; Phd, 2008) identified poor-performing athletes based on their behavioral patterns and analyzed the relationship between their behavior and performance.

In this paper, FCM analysis is applied to the analysis of athletes' psychological fitness. Through the training of FCM and neural network, the law and characteristics of athletes' positive psychological fitness are explored, and the potential relationship among various factors affecting psychological fitness is excavated, which provides a reference for universities to formulate corresponding strategies for early prevention and intervention of mental disorders.

3. Methodology

3.1 Feasibility of identifying athletes' psychological fitness problems driven

Big data helps to improve the efficiency of data analysis and processing of athletes' positive psychological fitness. Big data platform can break the limitations of traditional research methods, get the analysis results intuitively and quickly, not abnormal mental state more quickly, which is beneficial to master the overall mental state of athletes as well as individual mental state. With the growth of the times, mobile phones have become an indispensable mobile internet tool in people's lives, especially for athletes, who can't live, entertain and study without mobile phones. Therefore, using mobile phones as a medium can obtain a large quantity of athletes' daily behavior data. Driven by big data, many negative information and thoughts in the network have a bad influence on athletes, and this negative information easily lead to athletes' positive psychological problems. There are various factors that cause psychological problems, and the data of psychological fitness need to be analyzed from many aspects (H. Kim, Park, Kim, Kwon, & Kim, 2022). Psychological fitness data obtained from different angles respectively reflect different mental states. Under the background of big data, the psychological education of athletes is more targeted, which improves the effect of psychological fitness education. Big data technology is a remedy for the shortcomings of traditional survey sampling methods, and the survey is more convenient and quick, which can update and improve psychological fitness information, without the interference of external factors, improve the accuracy of information, and be more effective for the collection and analysis of psychological fitness information.

The mining and utilization of these data resources by big data can further quantify and de-experience the research of psychological fitness education (Ahn et al., 2018). Many surveyed athletes usually express unconsciously, which makes the data information more objective and accurate, and can reflect the psychological development and activities of contemporary athletes. The has a relatively relaxed environment, and it can hold activities freely in the university. These activities can better reflect athletes' psychological situation and publicize athletes' positive psychological fitness knowledge, which can record athletes' health status in detail. Big data technology can show athletes' psychological fitness status by analyzing various data indicators, which is helpful to intervene and deal with psychological fitness problems (Mph, 2012). Research on psychological problems through big data has great advantages, which can combine and compare individuals and groups, and study the psychological growth of individuals more comprehensively and truly (Wolpert et al., 2019). Under the background of big data, we can find out the psychological fitness problems of athletes in time and effectively, and formulate positive and effective

countermeasures to promote the growth of athletes' psychological fitness.

3.2 Analysis and mining of athletes' psychological fitness data

A well-planned data collection process is crucial in providing reliable sources for decision-making (DM). The reliability and persuasiveness of DM are enhanced by having an adequate number of data sets (Warner et al., 2011). The FCM (Fuzzy C-Means) algorithm is specifically designed for analyzing point sets within the eigenspace. Its objective function utilizes the sum of squared errors based on a similarity measure derived from the Euclidean distance. This objective function effectively handles data types with significant differences and dense data between classes. To mitigate the influence of noise data on initialization, the objective function incorporates information entropy, resulting in sample point membership functions exhibiting a Gaussian distribution. The cluster analysis process for athletes' psychological fitness analysis data is illustrated in Figure 1.

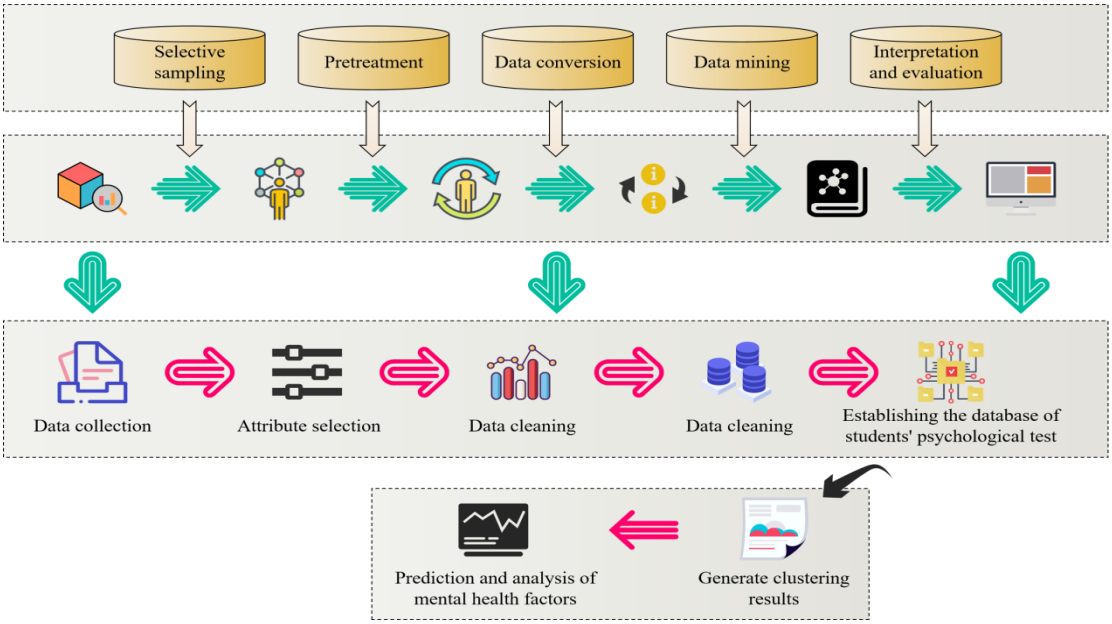


Figure 1: Cluster analysis process of athletes' positive psychological fitness analysis data

With the rise of digital campus, more and more athletes' behavior data are stored. These data have two characteristics, one is a large amount of data, the other is more complex and diverse. Assuming S is a set of s data samples, there are m category attributes with different values: $C_i(i = 1,2,\dots,m)$. Let s_i be the quantity of samples in class C_i. For a given sample, its total information entropy is:

$$I(s_1, s_2, \dots, s_m) = -\overset{i=1}{\overset{m}{a}} P_i \log_2(P_i) \qquad (1)$$

Where P_i is the probability that any sample belongs to C_i, which can

usually be expressed as s_i/s. Samples with attribute A value a_j in S are included in subset S_j. Let S_{ij} be the quantity of samples with the category C_i in the subset S_j. The information entropy value of the sample obtained by division is:

$$E(A) = \overset{j=1}{\overset{k}{a}} \frac{s_{1j}+s_{2j}+\cdots+s_{mj}}{s} I\left(s_{1j}+s_{2j}+\cdots+s_{mj}\right) \quad (2)$$

Among them:

$$I\left(s_{1j}+s_{2j}+\cdots+s_{mj}\right) = -\overset{i=1}{\overset{m}{a}} p_{ij}\, log_2\left(p_{ij}\right) \quad (3)$$

The probability of samples with category C_i in S_j subset is:

$$p_{ij} = \frac{s_{ij}}{s_{1j}+s_{2j}+\cdots+s_{mj}} \quad (4)$$

The information gain of sample set S obtained by division is:

$$Gain(A) = I(s_1, s_2, \ldots, s_m) - E(A) \quad (5)$$

If the value of information entropy becomes smaller, the value of information gain will become larger. Then the uncertainty of the test attribute A on the classification will become very small.

Artificial neural network processes information by imitating the structure of brain neurons. The best thing about it is that it can automatically find the corresponding relationship between the input data and the output data through training, and this learning process does not need to be controlled by anyone, only the training parameters need to be adjusted. Using clustering can not only find outliers, but also clearly know the value range of each attribute through clustering, so that the characteristics of outliers can be judged (B. Kim, Aronowitz, & DeMarco, 2019). By clustering, the subject attributes can be described, and the causes of abnormal data can be more fully explained. To some extent, the introduction of information entropy theory reduces the randomness of FCM algorithm in selecting the initial cluster. However, because FCM algorithm uses Euclidean distance to describe the location of the cluster, it can't express the irregular data set well, which will lead to a big error. Based on FCM algorithm based on information gambling, the idea of class merging can solve the problem well.

3.3 Assessment model of athletes' positive psychological fitness

In the assessment of athletes' positive psychological fitness, the DM method is used to analyze the deep psychological problems of athletes, evaluate the psychological fitness from a large amount of data, and find out the

factors that affect the psychological fitness, so as to help solve the psychological fitness problems of athletes. The algorithm for identifying athletes' psychological fitness problems based on multi-source data can identify athletes with psychological fitness problems to a certain extent. The time granularity of the data in the network log is accurate to the second, and the sequence obtained by establishing the behavior sequence directly according to the time sequence is different in length. Usually, athletes' online behavior is time-specific, and even the purpose of surfing the Internet in different time periods is generally different. All the clustering results are ultimately oriented to users, and users want the clustering results to be interpretable, understandable and available. Therefore, clustering may need to be associated with specific semantic interpretation and application. This section establishes a psychological fitness assessment model based on the classical learning and classification ability of neural network, and trains the network with a large quantity of classified samples, so that the network system with analytical ability can objectively evaluate psychological fitness. The multilayer neural network model is shown in Figure 2.

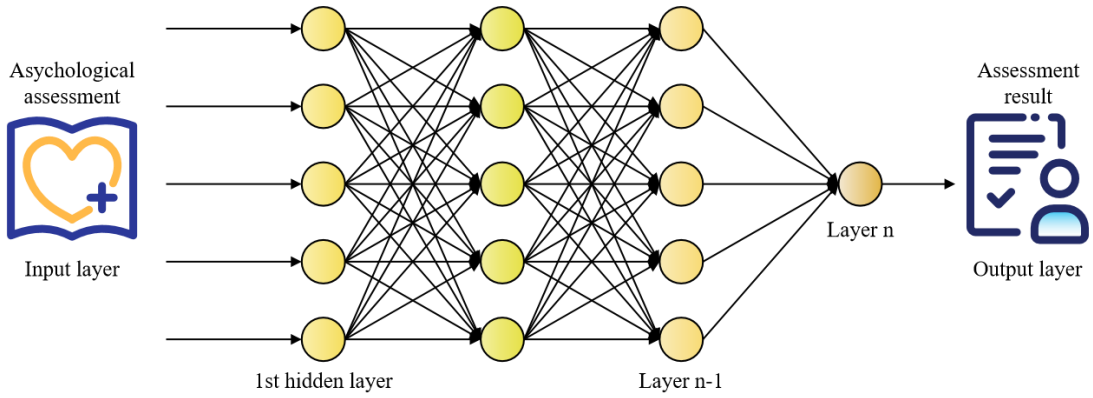


Figure 2: Multilayer neural network model

Standardized processing is also very important. Because the selected attributes all have different meanings, the data types may be different. A neural network improved by adaptive learning rate adjustment method is adopted;

$$\Delta X = lr \cdot \frac{\partial E}{\partial X} \qquad (6)$$

$$\Delta X(k+1) = mc \cdot \Delta X(k) + lr \cdot mc \cdot \frac{\partial E}{\partial X} \qquad (7)$$

In which lr is the learning rate and mc is the momentum factor. The added momentum term is essentially equivalent to the damping term, which reduces the oscillation trend of the learning process, thus improving the convergence and finding a better solution. Usually, the criterion for adjusting the learning rate lr is to check whether the correction value of the weight really

reduces the error function. If so, it means that the selected learning rate value is too small, which can increase the learning rate value. If this is not the case, and overshoot occurs, then the value of learning rate should be reduced. Because the linear relationship between the input vector $X(x_1, x_2, \dots, x_n)$ and the output vector is not satisfied, the unipolar sigmoid function is selected as the excitation function:

$$f(x) = 1/(1 + e^{-x}) \quad (8)$$

Set the factor set U and the assessment grade set V of psychoanalytic objects:

$$U = \{u_1, u_2, \dots, u_m\} \quad (9)$$

$$V = \{v_1, v_2, \dots, v_m\} \quad (10)$$

Fuzzy assessment is carried out on each factor in U according to the grade index in the assessment set, and the assessment matrix is obtained:

$$R = (r_{ij})_{n \times m} \quad (11)$$

In which r_{ij} represents u_i's membership degree with respect to v_i. After determining the importance index of each factor, record it as:

$$A = \{a_1, a_2, \dots, a_m\}, \quad \sum_{i=1}^{n} a_i = 1 \quad (12)$$

Synthesis:

$$\bar{B} = AR = (\bar{b}_1, \bar{b}_2, \dots, \bar{b}_m) \quad (13)$$

After normalization, the following results are obtained:

$$B = \{b_1, b_2, \dots, b_m\} \quad (14)$$

The analysis of athletes' psychological fitness data, first of all, is to collect athletes' psychological fitness data, select and clean up the data attributes, integrate effective data to establish a comprehensive psychological test database, and use FCM algorithm based on information entropy attribute weighting to cluster and analyze the data. It is of great significance to improve the efficiency of athletes' psychological fitness education by establishing the corresponding big data analysis platform for psychological fitness education, setting up athletes' psychological fitness service institutions, constructing athletes' psychological fitness education teaching mode, innovating athletes' psychological fitness education activities and improving the guarantee mechanism of athletes' psychological fitness education.

4. Result Analysis and Discussion

Big data itself does not generate value. How to analyze and use big data to help people and society is its value. The focus of psychological fitness education is data analysis, and the basis is data collection. Through the establishment of athletes' psychological fitness information database and archives, the psychological characteristics and laws of athletes are observed and analyzed. During athletes' psychological fitness education, it is essential to enhance the utilization of network and big data technologies. This involves creating psychological fitness data files for athletes and selecting appropriate neural network parameters to establish an optimal neural network model. The next step is to utilize a sample set to train the network, adjust the network weights, and evaluate the network's performance to ascertain if it meets the desired criteria. Subsequently, relevant sample data is processed to verify the attainment of expected goals, enabling intervention and addressing psychological fitness issues among athletes. A comparison between the output data generated by the psychological fitness assessment model and actual student data can be observed in Table 1 and Figure 3.

Table 1: Fuzzy neural network learning results

SAMPLE SET	PREDICTED VALUE	ACTUAL VALUE
40	0.824	0.836
80	0.796	0.81
120	0.771	0.785
200	0.863	0.877
240	0.81	0.822
280	0.82	0.832
320	0.845	0.859
40	0.824	0.836

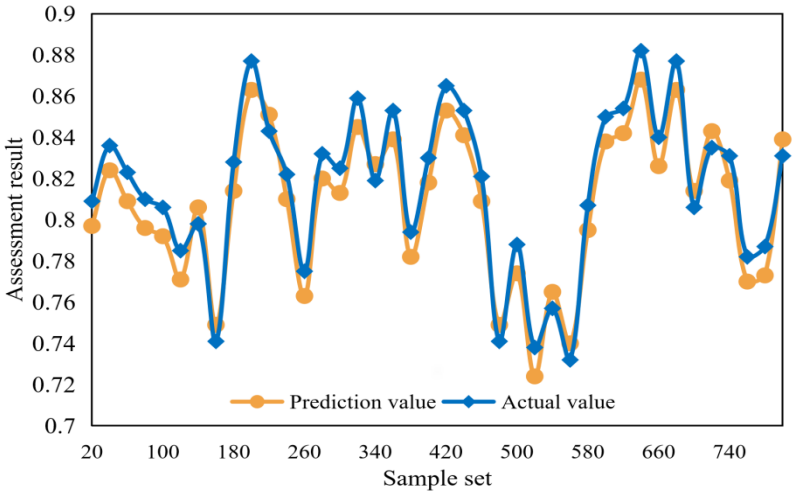


Figure 3: Learning results of fuzzy neural network

In practical work, psychological fitness educators should reasonably use

the relationship between data to predict and analyze, so as to accurately predict the future growth of athletes' psychology and further strengthen the psychological fitness educators' understanding of athletes' specific psychological conditions. In the network, a lot of data information will flow, which can truly reflect the psychological fitness of athletes. Therefore, a database of athletes' psychological fitness can be established, and more data resources can be collected, stored, acquired and shared to provide reliable support for athletes' assessment and assessment. Combining with the database of athletes' psychological fitness files, teachers can analyze athletes' psychological fitness, so as to supervise and manage athletes, find out their abnormal behaviors in time, and guide athletes in psychological aspects. In the data of athletes' psychological fitness assessment, incomplete data and invalid data are caused by athletes' carelessness or other reasons, which will lead to a lot of inaccurate noise data. Pretreatment of unsatisfactory data sources can greatly improve the execution efficiency and knowledge discovery process of FCM. The performance comparison results of athletes' psychological fitness assessment models after processing psychological fitness data are shown in Table 2 and Figure 4.

Table 2: Fuzzy neural network learning results

NUMBER OF NODES	FCM	SVM
20	1440	1447
40	1455	1543
60	1366	1362
80	1335	1371
100	1341	1376
120	1305	1369
140	1265	1102
160	1203	1062
180	1190	1017
200	1206	1016

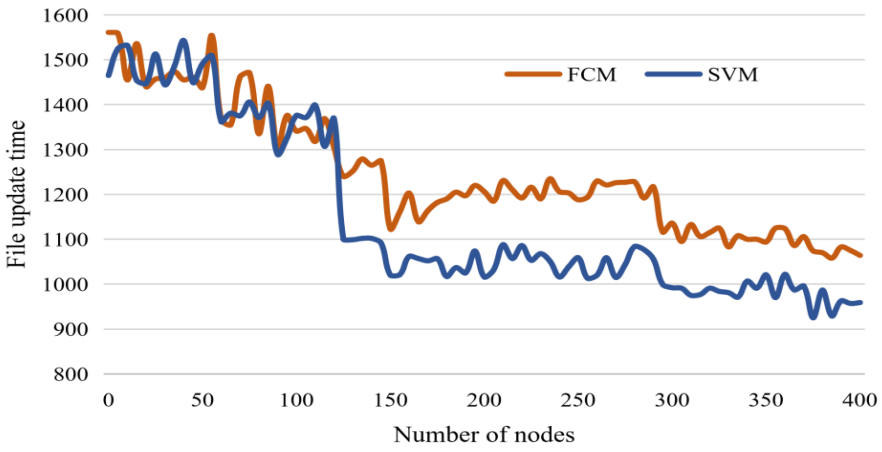
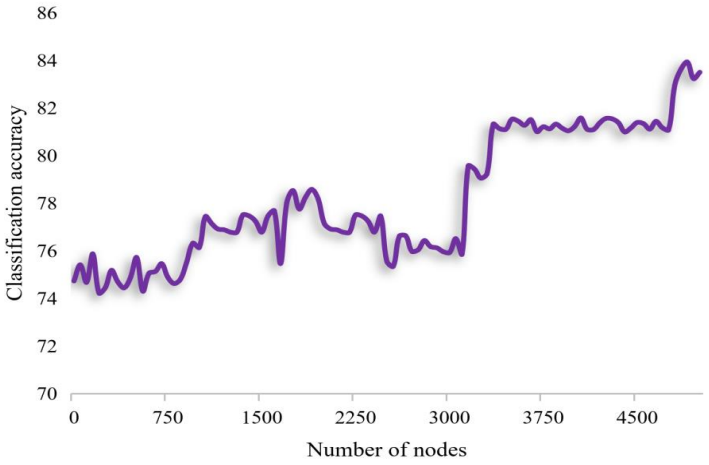
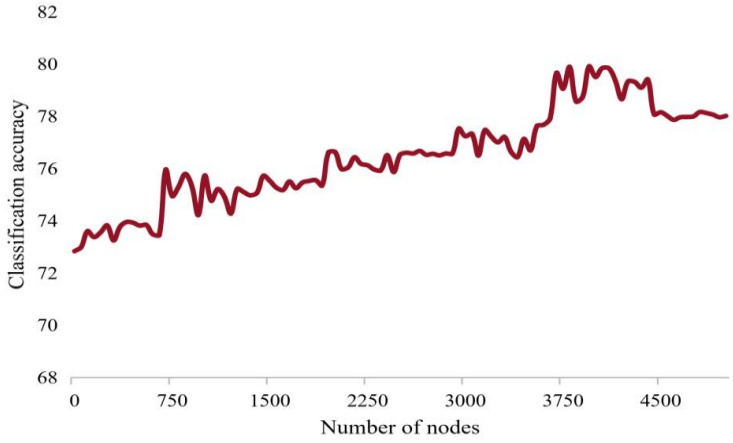


Figure 4: Performance comparison of algorithms

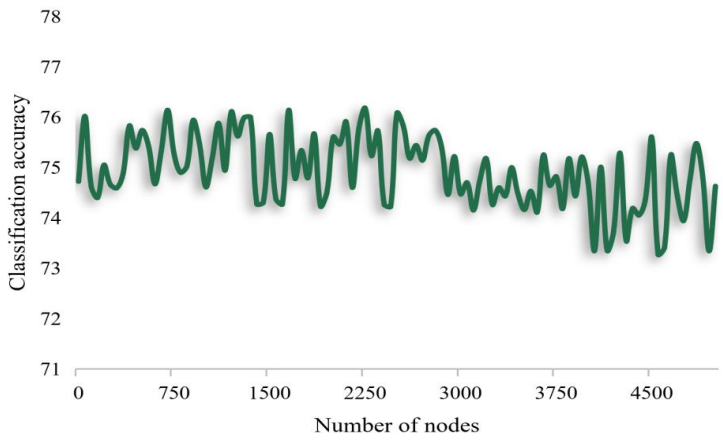
The establishment of a psychological archives database is a long-term endeavor that requires continuous updates, timely collection, and careful screening of data. Additionally, it necessitates scientific analysis, thorough summarization, and comprehensive evaluation. With the advent of big data, the volume of data continues to expand, underscoring the importance of effective information management and screening. It is crucial to promptly analyze and rectify data, ensuring the removal of false, outdated, and unsubstantiated information found on the network. Simultaneously, it is imperative to preserve authentic and reliable data information. By diligently managing and screening data, we can maintain the integrity and accuracy of the psychological archives database. The pre-alarm information is managed at different levels, and different levels of information are sent to different levels of staff, so as to establish and improve the dynamic tracking mechanism and management mechanism of psychological fitness, and lay the foundation for the smooth growth of the follow-up psychological fitness education for athletes. Under the information education mode driven by big data, the accuracy of different psychological fitness assessment algorithms in athletes' psychological assessment is shown in Figure 5.



(a) The positive psychological fitness assessment model of this paper



(b) SVM



(c) RF

Figure 5: Prediction accuracy of different algorithms in athletes' psychological fitness assessment

Leveraging the value of data can yield numerous benefits in optimizing resource allocation, enhancing decision-making capabilities, and boosting work efficiency within athletes' positive psychological fitness education. Furthermore, it can foster innovation in this field of work. To fully harness the potential of big data, it is crucial to establish and enhance a corresponding safeguard mechanism. This mechanism will enable us to effectively address the challenges associated with the utilization of big data. According to the results of big data screening and analysis, aiming at the universal problems, we should adhere to the combination of active intervention and self-adjustment, organically combine psychological fitness teaching with psychological fitness activities, realize the new educational and teaching goals of online and offline interaction and integration in and out of class, and promote the mutual integration and innovation of big data and athletes' psychological fitness education activities. Comparing the average absolute error and recall rate of the psychological fitness assessment model in this paper with the model in SVM, the results are shown in Figure 6 and Figure 7.

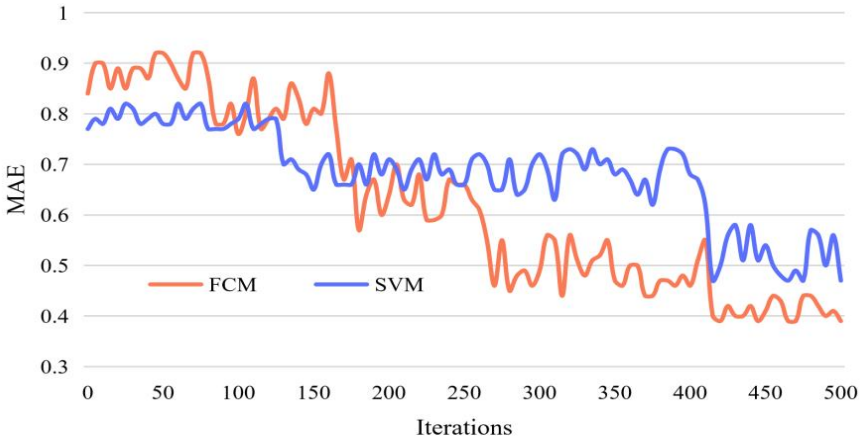


Figure 6: MAE comparison

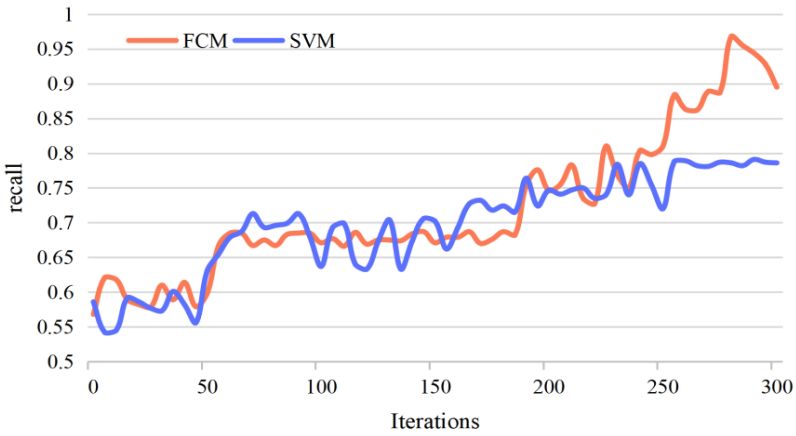


Figure 7: Comparison of recall rate

The comparison of Figure 6 and Figure 7 reveals that, following numerous iterations, this method outperforms the comparison algorithm in positive psychological crisis analysis. The error rate has been significantly reduced by 38.55%, and the recall rate has reached an impressive 96.87%, surpassing the comparison algorithm by 16.04%. Consequently, the assessment model of positive psychological fitness based on FCM and neural network proves to be a reasonable and feasible approach, holding immense significance for the advancement of positive psychological fitness education in universities. By employing scientific methodologies and enhancing the correlation of data information, it becomes possible to analyze variables within the data, gain a comprehensive understanding of athletes' basic information, and develop tailored positive psychological fitness education based on their backgrounds and specific information. In the process of psychological education counseling, we can create a good atmosphere for athletes, strengthen communication and exchanges with athletes, increase online activities, master athletes' psychology and needs, formulate targeted teaching plans, improve athletes' psychological quality and solve their psychological problems. Using big data in universities, we should establish a good platform for psychological fitness education, combine some actual cases and materials in athletes' lives, display them on the platform, and set up some authoritative links for athletes in need to understand and use, so that athletes can find solutions and coping methods based on their own problems.

5. Conclusions

On the basis of the wide application of big data in the field of positive psychological fitness, it has become an important research direction to use big data to study new ways of pre-alarm of psychological fitness crisis. In this paper, FCM analysis is applied to the analysis of athletes' positive psychological fitness. Through the training of FCM and neural network, the law and characteristics of athletes' positive psychological fitness are explored, and the potential relationship among various factors affecting psychological fitness is

excavated, which provides a reference to formulate corresponding strategies for early prevention and intervention of mental disorders. In comparison to the two existing psychological fitness assessment algorithms, this algorithm demonstrates notable advantages in terms of accuracy, reaching an impressive 91.26%. Through multiple iterations, this method exhibits significantly improved error rates compared to the algorithm used for psychological crisis analysis. In fact, the error has been reduced by 38.55%, while the recall rate has soared to 96.87%, surpassing the comparison algorithm by 16.04%. Consequently, this model offers a reliable foundation for psychological educators, thereby enhancing the efficiency and efficacy of school-based psychological counseling. By employing scientific methodologies and strengthening the correlation of data information, it becomes possible to analyze variables within the data, acquire essential athlete background information, and devise tailored psychological fitness education programs. Moreover, by harnessing big data analysis, educators can identify commonalities and individualities pertaining to athletes' positive psychological issues, leading to enhanced efficiency in addressing such problems and fostering the advancement of college psychological fitness education courses.

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