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Research Article

Analysis of Big Data Behavior in Sports Track and Field Based on Machine Learning Model

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At present, machine learning is more efficient and accurate for the efficiency of operation logic after four stages of reform. In order to improve the participation rate of the whole people in track and field sports and get a better level and ranking in track and field competitions, the ATI model under the machine model is used to deeply analyze the behavior of track and field sports in order to get more accurate data. There are a series of problems in the process of correlation analysis, such as the loss caused by the analysis process, the error in the analysis process, and the lack of understanding of track- and field-related data. In order to solve this series of problems, this study optimizes the behavior analysis through related experiments. The experiment proves the correlation between learning rate and loss. When the learning rate is 0.1, the loss caused by behavior analysis is lower. For the 23rd–28th session, the number of gold medals and the number of medals won in track and field were analyzed. By comparing the ATI model with the ATT model, ATT-Net model, and WAT model, it is concluded that the ATI model has a lower error rate for behavior analysis under big data. The coverage rate of behavior analysis data is wider. Therefore, in order to make track and field behavior analysis more accurate and stable under big data, the ATI model under machine learning should be preferred for data collection, collation, analysis, and summary. Through the ATI model to analyze the related behavior of track and field under big data, there are the following advantages: when the learning speed is 0.1, the loss value in the analysis process is reduced; the number of neurons is increased, and the dropout rate is reduced to reduce NPMSE value; and the error loss rate of behavior analysis is reduced, and the analysis coverage rate is increased.

1. Introduction

Through correlation analysis, we can get safer training methods and more accurate track and field data, so as to obtain better track and field results. In this study, the ATI model is proposed to analyze track and field data, and the error rate and coverage rate of the model are compared and analyzed. It is concluded that the ATI model under the machine learning model can be combined with big data to more accurately and stably analyze track and field behavior. By combining the behavior analysis model ATI with track and field sports, we can analyze more accurate and stable data, so as to increase the participation rate of track and field sports and analyze athletes' behaviors, reduce unnecessary sports injuries of athletes in the process of sports, and get better competition results.

In this study, various technical ports are used to solve technical problems. It qualitatively criticizes the extent to which the work under review meets these requirements, discussing the outstanding issues, and challenges in this area [1]. By studying the convenient technology brought by the related technical level, an online recursive algorithm for training support-vector machines is proposed, one vector at a time [2]. Data integration systems provide access to a large number of data sources through a single mediation pattern [3]. Machine learning tasks have become common in a wide range of fields and systems (from embedded systems to data centers) [4]. This study summarizes the current situation of deep machine learning and puts forward some views on how it may develop [5]. This study focuses on the statistical analysis of the results in the field of machine learning based on genetics [6]. They collect content from the web and organize it for easy access, retrieval, and search [7]. This study studies and analyzes the related track and field athletes, so as to reduce the accidental injuries of athletes. Microfracture is an effective first-line treatment, which can make young athletes with short symptom interval and less knee cartilage injury return to high-intensity track and field sports [8]. Preventive intervention should mainly focus on the overuse of injuries and full rehabilitation of previous injuries [9]. We report the incidence, risk, and severity of knee joint injuries across exercise, sex, and exposure type in high school [10]. Consistent use of definitions and methodological guidance will lead to more reliable and comparable evidence [11]. Future research needs to determine whether proving normal lower limb function before resuming exercise can effectively reduce the rate of reinjury [12]. Genes and environment are the basic and interdependent determinants of behavioral response [13]. These devices are inexpensive, easy to manufacture, reusable, and suitable for providing any liquid stimulation [14]. This study analyzes behavior through physical cognition, stress, and characteristics. The main goal is to overcome some of the main disadvantages of online communication, namely, the lack of contextual information such as body language or gestures [15].

2. Machine Learning Model and Track and Field Behavior Analysis

2.1. Machine Learning Model. There are four stages in the development of machine learning [16], as shown in Table 1.

Machine learning is based on physiology, cognitive science, and other studies on human learning mechanism [17]. Through GA, learning theory, analogy, induction, clustering, and other methods, machine learning is deeply studied and understood [18], as shown in Figure 1.

From Figure 1, it can be analyzed that the calculation methods related to machine learning are related to the computable determinacy of mathematics, the inductive analysis of philosophy, the study of the central nervous system in biology, the Bayesian judgment rules related to statistics, and the behaviorism of psychology.

Table 1: Development history table.

Stage	History of development
The first stage is the mid-1950s	Inspired by neurophysiology and biology, he mainly studies neural network system
The second stage is the early 1960s	Enlightened by psychology and human learning, it mainly obtains conceptual learning and language
The third stage is the middle and late 1970s	On the one hand, a large number of domain knowledge is introduced into the learning program; on the other hand, knowledge is acquired automatically
The fourth stage is the middle and late 1980s	Neural networks are emerging again, and multilayer neural networks and backpropagation algorithms are proposed to overcome the limitations of the early days

2.2. Correlation Behavior Analysis. Big data-related behavior analysis of sports track and field includes ideological education analysis, daily management analysis, and training and competition guidance behavior [19]. Among them, the analysis of ideological education includes the following: the analysis of will, morality, values, and other behaviors; daily management analysis includes the following: life, spirit, interpersonal analysis, etc.; the analysis of competition guidance includes the following: training, training plan, feedback, sports behavior, and other analysis contents [20], as shown in Figure 2.

The analysis of track and field behavior can analyze athletes' sports behavior, athletes' training methods, and athletes' psychological literacy. Through more accurate analysis of the statistics of the data and the analysis of the athletes' data, we can improve the athletes' behavior, psychology, and training methods, and get better results.

3. Correlation Formula

3.1. Machine Learning Model

3.1.1. Learning Theory. Output variable X and output variable Y form a joint distribution $F(X, Y)$, with L independent observation samples [21].

$$z = \{(x_1, y_1), (x_2, y_2), \ldots, (x_l, y_l)\}. \quad (1)$$

The probability measure $F(z) = F(x, y)$.

$$R(\alpha) = \int Q(z, \alpha) \mathrm{d}F(z). \quad (2)$$

Loss function variable z, α is as follows [22]:

$$Q(z, \alpha) = L(z, f(z, \alpha)). \quad (3)$$

The loss function is defined as follows:

$$L(y, f(x, \alpha)) = \begin{cases} 0, & y = f(x, \alpha), \\ 1, & y \neq f(x, \alpha). \end{cases} \quad (4)$$

If the output variable y is a real value, $f(x, \alpha), \alpha \in \wedge$ is a real function set.

$$\begin{aligned} L(y, f(x, \alpha)) &= (y - f(x, \alpha))^2, \\ L(y, f(x, \alpha)) &= |y - f(x, \alpha)|. \end{aligned} \quad (5)$$

Density estimation probability loss function is as follows:

$$L(p(x, \alpha)) = -\sum_{i=1}^{l} \log\, p(x_i, \alpha). \quad (6)$$

3.1.2. Learning the Concept of Consistency. $R(\alpha)$ is the universal function of minimizing risk [23].

For the same limit of function set and probability distribution function,

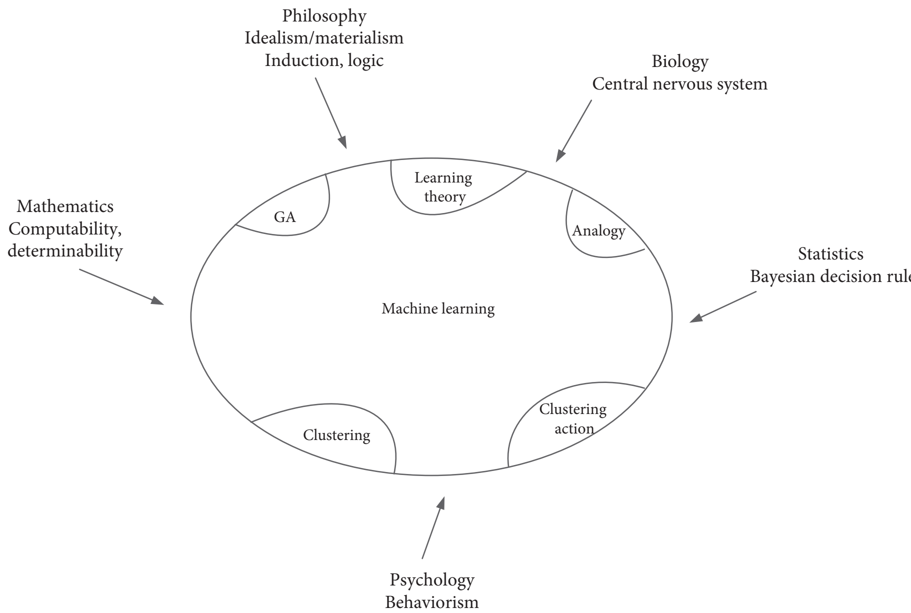

Figure 1: Machine learning model.

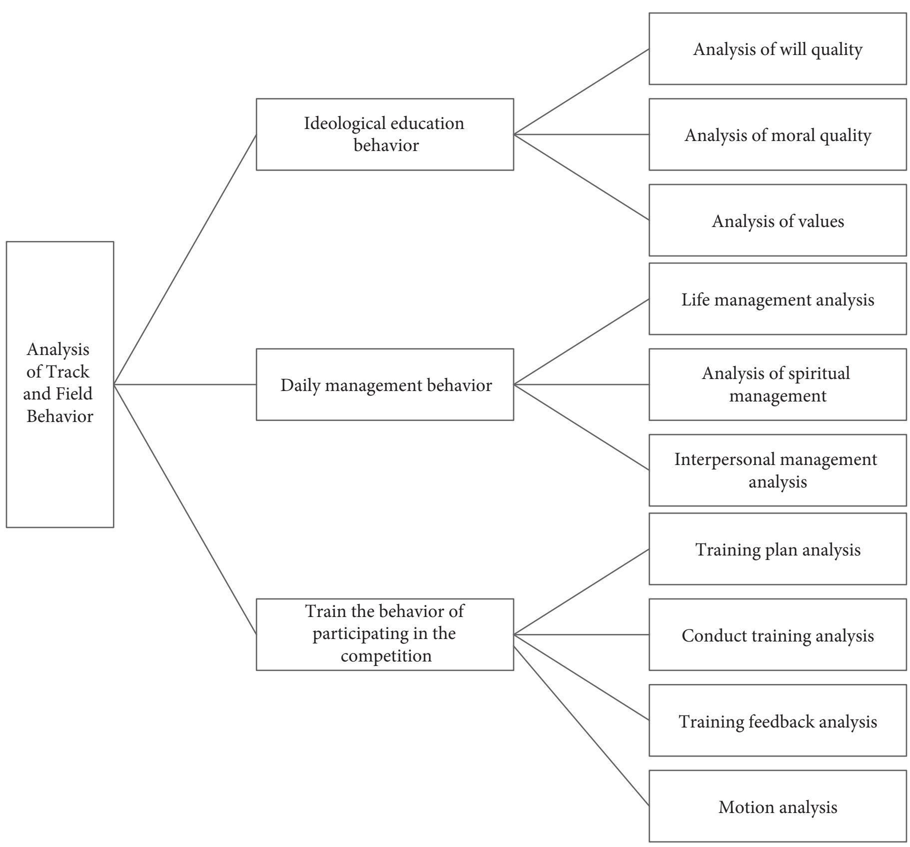

Figure 2: Track and field behavior analysis.

$$R_{\text{emp}} = \frac{1}{l}\sum_{i=1}^{l} Q(z_i, \alpha), \quad \alpha \in \wedge,$$

$$R(\alpha_l) \xrightarrow{l \longrightarrow \infty} \inf_{\alpha \in \wedge} R(\alpha_l), \tag{8}$$

$$R_{\text{emp}}(\alpha) \xrightarrow{l \longrightarrow \infty} \inf_{\alpha \in \wedge} R(\alpha).$$

Function $N^{\wedge}(Z_m)$ is defined as follows:

$$\begin{aligned} N^{\wedge}(Z_m) &= \max\{N(F, Z_m)\colon Z_m = \{z_1, \ldots, z_m\} \subset Z\},\\ VC\dim(Q) &= \max\{m\colon N^{\wedge}(Z_m) = 2^m\}. \end{aligned} \tag{9}$$

3.1.3. Milestones in Learning Theory. Sufficient conditions for consistency are as follows:

$$\lim_{l \longrightarrow \infty} \frac{H^{\wedge}(l)}{l} = 0. \tag{10}$$

Sufficient conditions are as follows:

$$\lim_{l \longrightarrow \infty} \frac{H^{\wedge}_{\text{ann}}(l)}{l} = 0. \tag{11}$$

Sufficient and necessary conditions are as follows:

$$\lim_{l \longrightarrow \infty} \frac{G^{\wedge}(l)}{l} = 0. \tag{12}$$

Minimization principle is as follows.

H is the VC dimension of the exponential function set, and L is the number of samples.

$$R(\alpha) \leq R_{\text{emp}}(\alpha) + \sqrt{\frac{h(\ln(2l/h) + 1) - \ln(\eta/4)}{l}}. \tag{13}$$

The relationship between empirical risk and actual risk is as follows:

$$R(\alpha) \leq R_{\text{emp}}(\alpha) + \Phi(h/l), \tag{14}$$

where $\Phi \propto h, \Phi \propto (1/l)$.

3.2. Big Data Analysis of Sports Track and Field

3.2.1. Gray Prediction of Track and Field Results.

$$X^{(0)} = \left[X^{(0)}(1), X^{(0)}(2), X^{(0)}(3), \ldots\ldots, X^{(0)}(n)\right]. \tag{15}$$

We calculate the stage ratio as follows:

$$Q(m) = \frac{X(m-1)}{X(m)}. \tag{16}$$

We calculate to obtain the following:

$$\begin{aligned} Q &= (Q(1), Q(2), \ldots, Q(n)),\\ Q(m) &\in \left(e^{-2/n+1}, e^{2/n+1}\right). \end{aligned} \tag{17}$$

We solve coefficients by the least squares method.

$$u = \begin{pmatrix} a \\ b \end{pmatrix} = \left(B^T B\right)^{-1} B Y^T. \tag{18}$$

We get the response function as follows:

$$\hat{X}^{(1)}(m+1) = \left(X^{(0)}(1) - \frac{b}{a}\right)e^{-am} + \frac{b}{a}. \tag{19}$$

Data restoration through first-order cumulative reduction is as follows:

$$\hat{X}^{(0)}(m+1) = \hat{X}^{(1)}(m+1) - \hat{X}^{((1)}(m), \quad m = 1, 2, 3, \ldots. \tag{20}$$

3.2.2. Relative Error Test Steps. We find relative residuals as follows:

$$e^{(0)}(m) = X^{(0)}(m) - \hat{X}^{(0)}(m). \tag{21}$$

We calculate the relative residual rate as follows:

$$P\left(e^{(0)}(m)\right) = \frac{e^{(0)}(m)}{X^{(0)}(m)} * 100\%. \tag{22}$$

We calculate the average residual rate as follows:

$$P\left(e^{(0)}(\text{avg})\right) = \frac{1}{n-1}\sum_{m=2}^{n}\left|e^{(0)}(m)\right|. \tag{23}$$

4. Machine Learning and Behavior Analysis

4.1. ATI Machine Learning Model

4.1.1. Loss Curve Analysis of ATI Model. In order to analyze the related data of sports track and field, this study proposes the ATI model under machine learning (ML) to analyze the behavior of big data [24]. The loss curve of the ATI model is analyzed by designing experiments. In the iterative epoch of 0–500 learning rates, loss experiments are carried out on learning rates of 0.0001, 0.001, 0.01, and 0.1, respectively, to obtain correlation loss values. From the images, when learning rates are 0.001, 0.01, and 0.1, respectively, the loss value of the correlation curve greatly decreases, shows a gradual downward trend, and gradually tends to be stable. Experiments and data show that when the learning rate is 0.1, the loss gradually decreases from 0.00025 when the iteration era is 0, 0.0002 when the iteration era is 100, 0.0001 when the iteration era is 200, and the loss of the ATI model decreases to zero when the iteration era is 300, and the loss is zero when the iteration era is 400 and 500, indicating that the loss rate of the ATI model decreases to zero when the iteration era is 300 [25]. When the learning rate is 0.01, the loss rate in 0–200 iteration era is similar to that in 0–200 iteration era, the loss is 0.00015 when the iteration era is 300, 0.0001 when the learning rate is 400, and the loss drops to zero when the iteration era is 500. When the learning rate is 0.0001, the loss is higher, which is 0.0014 at 300 era, 0.0005 at 400 era, and 0.0003 at 500 era. Therefore, in order to

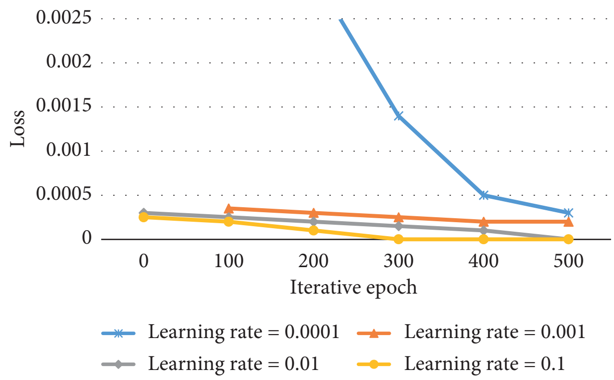

Figure 3: Loss analysis table.

minimize the loss, the ATI model proposed in this study should be used. When the learning rate is 0.1, the corresponding loss is lower than other learning rates. When the learning rate is 0.0001, the loss is too serious, which will easily lead to an inaccurate analysis of related behaviors, as shown in Figure 3.

4.1.2. ATI Machine Learning and Hidden Neurons. Through relevant experiments and data, it can be seen that when the number of hidden neurons is fixed, the analysis of the dropout rate and NRMSE data shows that when the dropout rate is from 0 to 0.9, the NRMSE value approximately gradually increases, and when the dropout rate is 0.9, the NRMSE value reaches the highest value of 0.8. When the number of neurons increased from 8 to 16, 24, and 32, the NRMSE value gradually increased with the increase in the dropout rate. When the number of neurons was 16, the highest NRMSE value was 0.75 when the dropout rate was 0.9. When the number of neurons is 24 hours, with the increase in the dropout rate, the NRMSE value also gradually increases, reaching the highest value of 0.4 at 0.9. As shown above, when the number of neurons is 32 and the dropout rate is 0.9, the highest NRMSE value is 0.3. On the other hand, when the dropout rate is fixed and the neural network gradually increases, the NRMSE value gradually decreases. According to the experiment and related data, the following conclusions are drawn: when the dropout rate is constant, with the increase in hidden neurons, the NRMSE value gradually decreases. When the number of hidden neurons is constant, the NRMSE value gradually increases with the increase in dropout rate. This shows that the relationship between the ATI machine learning model and NRMSE value is related to the number of hidden neurons and dropout rate. When the number of neurons increases to 32, the lower the dropout rate, the lower the NRMSE value, and vice versa, as shown in Figure 4.

4.2. Analysis of Sports Track and Field

4.2.1. Big Data Analysis of Track and Field Performance. The number of medals, gold medals, silver medals, and bronze medals is statistically analyzed through the number of track and field competitions. In the 24th competition, the

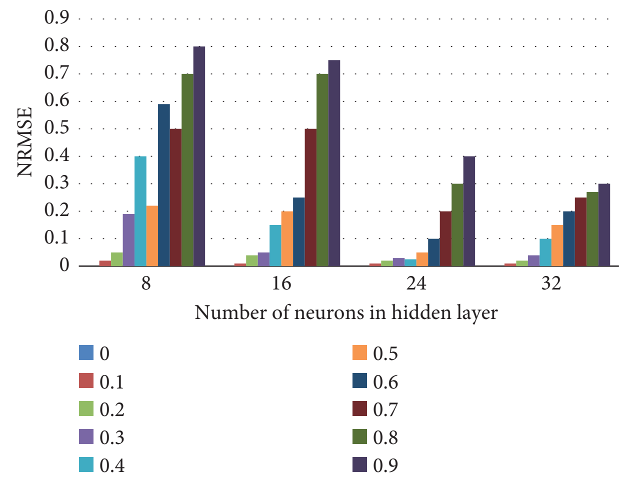

Figure 4: NRMSE data analysis.

total number of medals won was 1, which was the bronze medal won by the shot put competition. In the 25th competition, the total number of medals won was 4, including 1 gold medal, a silver medal in walking race and shot put competition, and a bronze medal in walking race and middle and long-distance running, respectively, totaling 4 medals. In the 26th competition, he won a gold medal in middle and long-distance running, a bronze medal in middle and long-distance running and shot put, respectively, and a bronze medal in walking race, totaling 4 medals; Won a gold medal in walking race in the 27th competition. In the 28th competition, he won two gold medals in hurdle and middle and long-distance running, respectively. In the 23rd to 28th competitions investigated, a total of 13 medals were won. As shown in Table 2.

Through relevant investigation and data drawn into the icon, the number of participants, the number of top eight, and the number of gold medals in the 23rd to 28th track and field competitions were statistically analyzed. According to the chart, the number of participants will be 22 in the 23rd session, which is the least in the survey session. By the 28th session, the number of participants will be 52, which has been greatly improved. It shows that with the development of the times, track and field are known and liked by more people, and the promotion of track and field events has played a role in promoting national fitness. Through the analysis of the overall data, it can be seen that from the 23rd to the 28th, track and field sports have been better popularized, and more people have participated in them, as shown in Figure 5.

According to the analysis of the number of people who entered the top eight in the competition, in the 24th to 25th sessions, from 27th to 28th, it showed an upward trend. At the 25th time, the number of people entering the top eight competitions reached the highest of 12 in the survey session, the lowest is the 27th session, and only three people enter the top eight of the competition. According to the relevant data, there is no obvious rule in the number of people entering the top eight, which shows that in the track and field competition, the participants are unstable. It is necessary to

Table 2: Analysis of the number of medals.

Number of sessions	Gold medal (pieces)	Silver medal (pieces)	Bronze medal (pieces)	Total medals (medals)
23rd session	0	0	1 (high jump)	1
24th session	0	0	1 (shot put)	1
25th session	1 (race walking)	1 (shot put)	2 (race walking, and middle and long-distance running)	4
26th session	1 (middle and long-distance running)	2 (middle and long-distance running, and shot put)	1 (race walking)	4
27th session	1 (race walking)	0	0	1
28th session	2 (hurdle, middle, and long-distance running)	0	0	2
Total	5	3	5	13

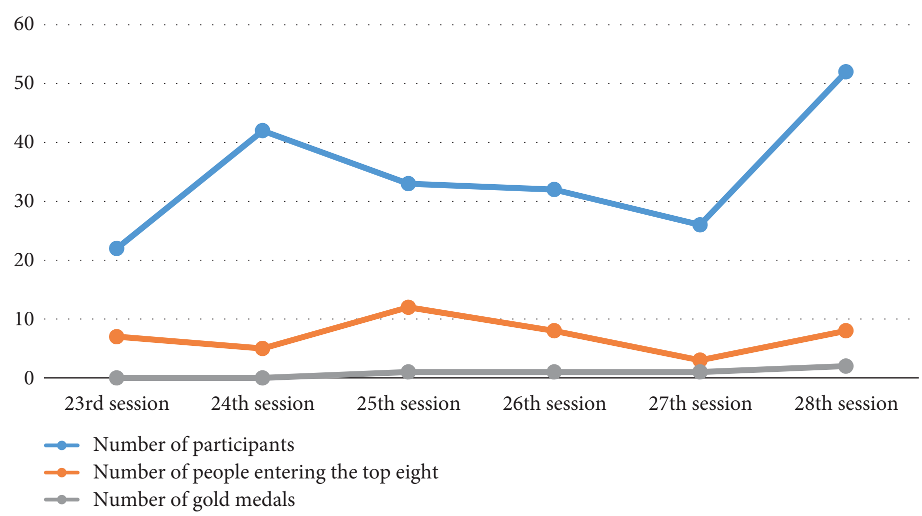

Figure 5: Track and field data statistics.

strengthen the behavior analysis of sports track and field big data in order to carry out training reform in track and field training. Through the data analysis of the number of gold medal winners, it can be seen that the number of gold medal winners in the 23rd to 28th track and field competitions is on the rise, the number of gold medals in the 23rd and 24th track and field competitions is 0, the number of gold medals in the 25th to 27th track and field competitions is 1, and the number of gold medals in the 28th track and field competition is 2.

4.2.2. Data Analysis of Men's Track and Field. In order to accurately analyze the related behaviors of sports track and field big data, this experiment makes a more accurate behavior analysis through statistical analysis and comparative analysis of men's track and field-related data, so as to make more right people join the track and field competition. Linear 100 m, linear 200 m, and linear 400 m curve data are obtained by calculating relevant data. Compared with linear data, the absolute data of linear 100 m, linear 200 m, and linear 400 m are 2.1, 2.25, and 1.1, respectively, while the average progressive coefficient of 100 m, 200 m, and 400 m is $2.25 > 2.1 > 1.1$, indicating that the stability of 200 m performance is greater than 100 m and 400 m. Through experiments, the behavior analysis of 200-meter training mode under big data is carried out, and the training mode of 100-meter and 400-meter men's track and field competition is improved according to the results of relevant behavior analysis, so as to improve the performance and stability of 100-meter and 200-meter running, as shown in Figure 6.

Through the analysis of the relevant data in Figures 6 and 7, it can be known that the women's 100-meter, 200-meter, and 400-meter track and field sprint results are more stable than those of men. Therefore, from the results of correlation analysis to find out the differences between men's and women's training methods, in order to improve men's track and field training, the training results are made more stable.

4.2.3. Data Analysis of Women's Track and Field. The experiment is shown in the following figure. By studying and analyzing the fixed-base ratio of linear 100 m, linear 200 m, and linear 400 m in women's track and field, and then comparing and analyzing the results of 100 m, 200 m, and 400 m with the fixed-base ratio, the behavior analysis of the performance stability and changing trend is carried out. Through relevant research, calculation, and analysis, it is known that the absolute values of linear 100-meter, linear 200-meter, and linear 400-meter fixed-base ratio scores are

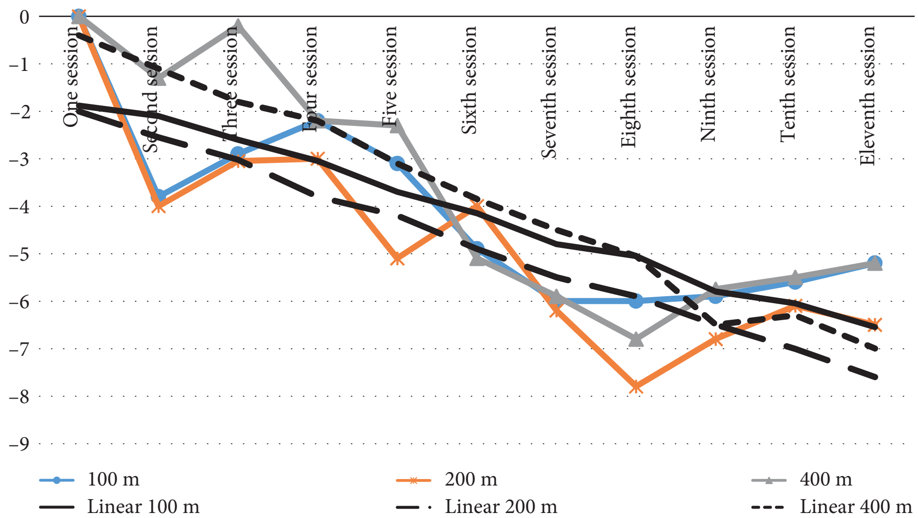

Figure 6: Analysis of men's track and field.

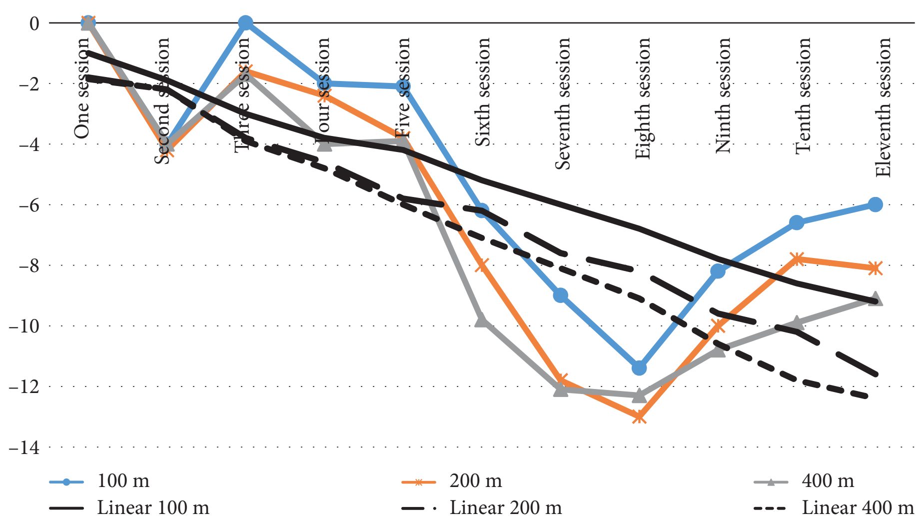

Figure 7: Analysis of women's track and field.

1.9, 2.2, 2.2, and 2.2 > 1.9 respectively, which shows that women's 400-meter and 200-meter scores are more stable than 100-meter scores. From the average progression coefficient of sprint, we can see that the absolute value of women's events is greater than the average value of men's events, which shows that women's track and field sprint performance is more stable than that of men. Through the experiment and the development trend of the image curve, it can be seen that the absolute value of the fixed-base ratio of women's track and field sprint in 100 meters, 200 meters, and 400 meters that reached the highest in the 8th competition, with the results of 10.93 s, 22.33 s, and 50.69 s, respectively. In order to make track and field performance more stable and shorten the time, the ATI model under machine learning should be used to analyze related sports behaviors through track and field big data, so as to improve the stability of track and field performance and shorten the competition time, as shown in Figure 7.

4.3. Comparison of Analysis Models

4.3.1. Error of Data Behavior Analysis. In order to analyze the error rate of the ATI model under machine learning in track and field big data behavior analysis, the model is analyzed through 1000, 2000, 3000, 4000, 5000, and 10000 data. It can be seen from the experimental data that, when the amount of data is increasing, the error rate of the ATI model, ATT model, ATT-Net model, and WAT model for behavior analysis is slightly increased, but the error rate of the ATI model proposed in this study is lower than that of the other three models. Therefore, the results obtained by the ATI model proposed in this study for behavior analysis of track and field big data are more accurate. Through the ATI model to track and field athletes' behavior analysis, from many aspects to improve the athletes' behavior, the stability of sports performance is improved and the competition time is shortened, as shown in Table 3.

Table 3: Behavior analysis data sheet.

Model	Behavioral analysis data	1000 (%)	2000 (%)	3000 (%)	4000 (%)	5000 (%)	10000 (%)
ATI	Error rate	2	2.40	2.70	3.50	3.60	3.30
ATT		2.40	3	3.70	4.60	5	5.40
ATT-net		2	3.10	3	4.50	6	5.50
WAT		7	7.30	8	8.40	11	11.30

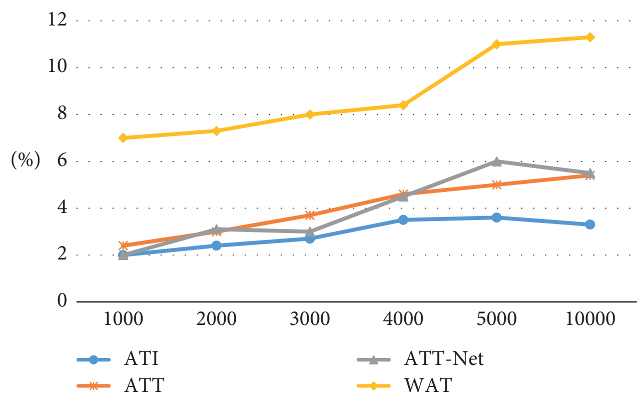

Figure 8: Error rate analysis.

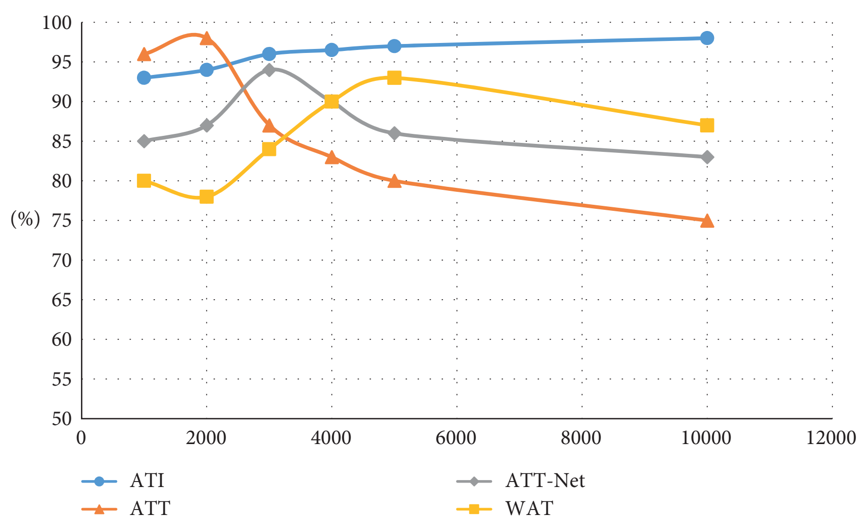

Figure 9: Coverage analysis.

Through the related experiments to draw experimental graphics, from the curve movement trend of the image, it can be seen that in the analysis of 1000–10000 behavior data, with the increase in data, the error rate of the comparison model slightly increases, showing an upward trend. But through the correlation image curve, we can see that the ATI model curve is always at the bottom, which shows that the error rate of the ATI model is the lowest under the condition of increasing behavior data, and it is more accurate for correlation behavior analysis, as shown in Figure 8.

4.3.2. Coverage Analysis of Big Data Behavior Analysis. Through the ATI model, ATT model, ATT-Net model, and WAT model, the coverage of big data behavior analysis is analyzed. Through the relevant experimental analysis of the relevant information, the ATI model for behavior analysis coverage of 1000–10000 will be carried out in coverage analysis, and error rates in this range are small or neglected. For the ATT model, the analysis coverage rate is about 1000–3000, and there is a high accuracy rate in this coverage range, but when the big data behavior increases, there is a large error in the error rate. For the ATT-Net model, its coverage rate is about 2000–5000, and there is a high accuracy rate in this range. The coverage rate of the WAT model is within 4000–10000 data analysis, but the accuracy rate is relatively unstable when there are few data behavior analyses. Therefore, to sum up, the ATI model has wider coverage ability, higher accuracy, and relatively stable error rate within its coverage range, while the ATT model, ATT-

Net model, and WAT model have a coverage shortage range, and the behavior analysis outside the coverage range is unstable. Therefore, in order to obtain stable and more accurate behavior analysis of big data, the ATI model should be preferred to analyze behavior data, as shown in Figure 9.

5. Conclusions

In this study, the loss of the ATI model and the correlation analysis of learning rate, through the experiment and related data can be seen when the learning rate is 0.1, the loss is the lowest, when the learning rate is 0.0001, the loss is higher, and in order to reduce the unnecessary loss in the experimental process, we should give priority to the learning rate of 0.1 for the experiment. Next, the ATI model proposed in this study explores the change in NRMSE value when the hidden neurons and dropout rate change. The results show that when the number of neurons is fixed, the NRMSE value also increases with the increase in the dropout rate, and when the dropout rate is constant, the NRMSE value decreases with the increase in hidden neurons. Finally, the ATI model and other models for error rate and behavioral analysis coverage comparative analysis draw the conclusion that the ATI model compared with the rest of the model error rate is lower and has more extensive coverage. For track and field big data behavior analysis under the machine learning model, in order to improve the accuracy and stability of related behavior analysis, this study proposes the ATI model under machine learning. Through the analysis of the ATI model, the sports mode and arrangement are improved to get better results.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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