

Research Article

Application of Multisource Big Data Mining Technology in Sports Economic Management Analysis

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The sports economy also occupies a main part of the national economy, which requires professionals to be able to evaluate the development of the sports economy. The sports industry will generate cumbersome data, which are important for the future development trend of the sports economy. This research will collect a large amount of data from the sports industry, data mining technology, and neural network method that will be used to fully mine and predict the relationship between sports economic data, and it will provide corresponding management references for sports industry companies. Some important statistical parameters will be used to evaluate the feasibility of data mining techniques and neural network methods in sports economic management. The research results show that the error of data mining technology in the classification of sports economy is within 2.54%, and the prediction error of the neural network method is also within 3.2%. This shows that the data mining technology proposed in this study is feasible for classification and prediction application in sports economic management. Once the forecast data of the sports economy are output through the output layer, the sports economy managers can rely on these data to manage and adjust the relevant factors of the sports economy.

1. Introduction

With the continuous improvement of economic strength, people's living standards have undergone great changes [1]. People pay more and more attention to life and health issues, and sports is a typical representative of development. With the continuous development of the sports industry, it has gradually become a business model. People are not just pursuing sports, but they have begun to pursue videos, products, and stars brought by sports, which has led to the rapid development of the sports industry [2–4]. The development of sports not only symbolizes the embodiment of a country's comprehensive strength, but also it also reflects the living standards of the people. The development of the sports industry also drives the development of the national economy, which is also an important aspect of economic development. The development of the sports industry has also led more people to actively participate in sports, not only exercising, but also pursuing sports brands and watching games [5]. The ways of participating in the sports

industry have become more diverse. People's active participation in the sports industry has driven the rapid development of the sports economy, and the development of the sports economy has also provided people with more sports participation models. It will give people more joy and happiness in life, and it is a two-way process [6, 7]. More and more countries are participating in international sports events, which not only reflects the development of a country's comprehensive strength but also drives the development of national comprehensive economic strength [8–10]. Therefore, the development of the sports industry is an important factor for a country or an individual.

The development of the sports industry will inevitably bring about many influencing factors [11]. The development of the sports industry is different for different countries and different sports. More and more researchers and sports industry developers have actively participated in the study of sports economic development, because the sports industry is an international industry, such as the NBA, World Cup, and other sports events [12, 13]. It is no longer confined to the

country or a small sports industry. If the relationship between the elements in the process of sports economic management can be well handled, it will be beneficial to the long-term development history of sports industry companies. There will be very complex data in the process of sports economic management with the globalization of the sports industry [14]. There are complex relationships between these data, but relying solely on sports industry company employees to process this data is a tricky task [15]. The development of sports industry companies is not only limited to the profit and loss status of their own companies but also involves factors such as advertising and marketing, product effect income, and so on. Similarly, with the improvement of people's living standards, their pursuit of sports is not only to participate in physical exercise themselves but also to pursue their favorite sports teams and stars, etc., this will drive the development of stadium facilities and revenues, and it will also drive the sale of related sports products [16–18]. For the large sports industry companies, this also involves the development trend of the company stock.

The complex data of the sports industry require a new type of processing method for efficient processing. The data mining method is a new type of product in recent years. It is an inevitable product with the development of intelligent technology and the development of high-performance computers [19, 20]. These data mining algorithms can use computer technology and nonlinear algorithms to process and mine data. It can not only replace professional technicians to process data, but it also can find more potential data correlations that cannot be found by expertise and experience. With the development of hardware equipment, data mining technology has appeared many types of algorithms, which are suitable for different research objects. These algorithms include reinforcement learning, neural network methods, and methods such as clustering and decision trees. These algorithms can perform both classification and regression tasks. Data mining methods can well map the relationship between input and output with complex relationships. Similar to the data generated by the sports economic industry, professionals can only find a small part of the relevant information using empirical knowledge and mathematical formulas. However, the data mining method can fully excavate some potential information, which can well guide the economic development and future development trend of the sports industry. For any industry, data mining methods will have better applicability and accuracy, which require them to find suitable algorithms and hyperparameter combinations.

Data mining methods can help managers of sports industry companies to find the correlation between complex data, and this can instruct the managers of the sports companies to make the guiding decision on the present situation and the future development trend of the sports economy. The development of the sports industry is closely related to the marketing of sports products, the marketing of stadium, the investment of advertising, and the operation of employees. But it can be a tricky and difficult task to rely on the experience of managers to process the data and find the connections between them. For the data mining method, as

long as the professionals train to complete the sports economic management model, it can quickly and efficiently complete the sports economic data processing and forecasting tasks. It can greatly save human and material resources, and the accuracy of this method is higher than the artificial means. Data mining is mainly to mine the correlation and potential information between data, which includes many algorithms, such as decision tree and neural network methods.

The multisource data of the sports economy were used to classify and predict by using data mining methods and neural network methods. This study will introduce five aspects. The first part mainly explains the trend of sports economic development and big data development. The second part mainly introduces the development status of sports economic management-related research. The third part introduces the multisource data sports economic management forecasting model proposed in this study. The fourth part is the focus of this study. It mainly introduces the feasibility of data mining methods and neural network methods in the classification and prediction of sports economic data using various statistical parameters. The fifth part is the summary part.

2. Related Work

Sports economic management-related industries have rapidly developed in the world, which is an important aspect of the improvement of national economic strength. Many researchers have carried out a lot of research. Yang et al. [20] proposed a nonlinear entropy coupling evaluation model of sports economy based on the coordination degree of regional development, social environment, and sports economy. They analyzed the feasibility and validity of GMM in sports economic evaluation based on MATLAB software and provided a reference for the stable development of the sports economy. Mou et al. [7] combined internet technology with sports economic management to study the effect of industry on sports economic development. Based on the OpenStack cloud platform, they used big data technology to study the impact of the development of the sports industry on the economy of China. The results show that the development of sports economy has contributed 11% and 7% to the development of the economy of China. Big data technology based on cloud platform also promotes the research of the sports economy. Cheng et al. [21] used cloud platform technology and big data technology to analyze the development trend of sports economy, and their research on sports economy provided new ideas. They used the Hadoop cloud platform processing data system and support-vector machine algorithm to perform regression processing on sports economic data. The research results show that the sports economy correlation of big data analysis is 0.5155, and the data analysis technology based on cloud platform technology is beneficial to the development of the sports economy. Zhang [22] argued that the current sports-economy complex system (SECS) ignored the differences between different subsystems and differences between different characteristics. He studied the simulation and

verification model of SECS based on complex system theory, which mainly studies the relationship between regional development and sports economy. At the same time, it introduced the accelerated genetic algorithm (AGA) as the evaluation index of the coordination relationship between sports economy and regional development. The findings suggested that this approach is feasible for the sports economy. Some researchers have also conducted related research on sports economy using big data technology. Yang [23] saw that the vigorous development of the sports economy has brought the great potential to the improvement of the country's comprehensive economic strength. He used the data mining method of big data technology to study the forecasting model of the sports industry. The research results show that the neural network method has good accuracy and robustness in predicting the sports economic industry. Shao and Sun [24] believed that the coastal tourism industry has rapidly developed, but the development of the sports tourism industry is relatively slow. According to the advantages and characteristics of the coast, they used the SWOT method to study the impact of sports economic development on the development trend of coastal tourism. Huo [25] believed that listed companies in the sports economic industry are an industry that has only recently emerged, and China's listed companies in the sports industry are relatively weak. He analyzed the development trend of China's sports economy and the necessity of the sports industry for China's comprehensive economic development from the perspective of the economic strategy of listed companies. The research results showed that the listing of sports economy will promote the development of China's comprehensive economic strength. Wang [26] saw that the esthetic economic theory will promote the development of the sports economic industry, but there is currently a lack of comprehensive evaluation models and indicators. He used the K-means method to evaluate and predict the consumption capacity of sports economic data. The results show that the prediction accuracy of the improved algorithm is above 95%. The degree of fit between the evaluation indicators also reached 98%. Through literature review, it can be seen that data mining methods are rarely used in the field of sports economic research, and the current related research on sports economics is still concentrated on traditional methods. This study mainly uses a decision tree and the neural network method to predict the important factors in sports economic management, which can provide a reliable basis for sports economic management.

3. Introduction to the Classification and Prediction Methods of Sports Economic Multisource Data

3.1. A Survey of Data Mining Methods. The data mining method has obvious advantages in finding the correlation between data and mapping the relationship between complex data. It is an important product in the computer field in recent years. The field of sports economic industry is also rapidly developing, which will generate a large amount of

cumbersome data, which requires higher-performance algorithms to automatically process these multisource data instead of manual methods [27]. It can not only improve the efficiency and accuracy of multisource data processing in the sports economic industry but also process higher-dimensional data. Data mining methods have produced many types for different research objects, such as decision trees, clustering, and neural network methods. They have good performance and advantages in regression tasks and classification tasks [28]. To find a data mining method suitable for sports economics requires continuous trial and hyperparameter tuning.

3.2. The Process of Multisource Data Classification and Prediction of Sports Economic Industry. Figure 1 shows the workflow of the data mining method in dealing with the classification and prediction of multisource data in the sports economic industry. First of all, this research needs to preprocess the collected data on sports advertising expenses, sports product marketing status, and sports ticket revenue. These preprocessed multisource data will be processed into data that conform to the uniform distribution and the same magnitude, and these data will be used as learning samples for the decision tree algorithm. They will be processed into labeled data for relevant learning and classification processes. Finally, these multisource data will be divided into five types of data required for this research, and these data will be further used as the input data of the neural network algorithm. These multisource data will complete the prediction and classification tasks of sports economic industry data through this workflow.

Data mining methods are divided into many types according to different research data types, and they have different accuracy and robustness in different research tasks [29, 30]. This study will choose a decision tree as the classification task of sports economic multisource data. Figure 2 shows the workflow of the decision tree in the multisource data classification task of the sports economy. Figure 2 is just a schematic diagram of a decision tree for multisource data in the sports economy. The branch of the decision tree selected in this study is 5, which represents that the multisource data of the sports economy will be divided into five categories, which represent the five categories of related factors that include sports advertising expenditures, sports ticket revenue, sports-related product sales, administrative expenses, and others. Each decision tree will have a different number of branches, which represents the number of branches in the decision tree. Too many branches will affect the computation time and generalization ability. Too few branches can also affect the classification accuracy of sports economics. This study will choose 3 as the number of branches of the decision tree.

Different data mining methods will have different evaluation indicators. For decision trees, entropy is one of the most important evaluation metrics. Equation (1) shows the entropy calculation process. The smaller the entropy value, the better the classification effect.

$$H(D) = - \sum_{l=1}^L \frac{|C_l|}{|D|} \log_2 \frac{|C_l|}{|D|}. \quad (1)$$

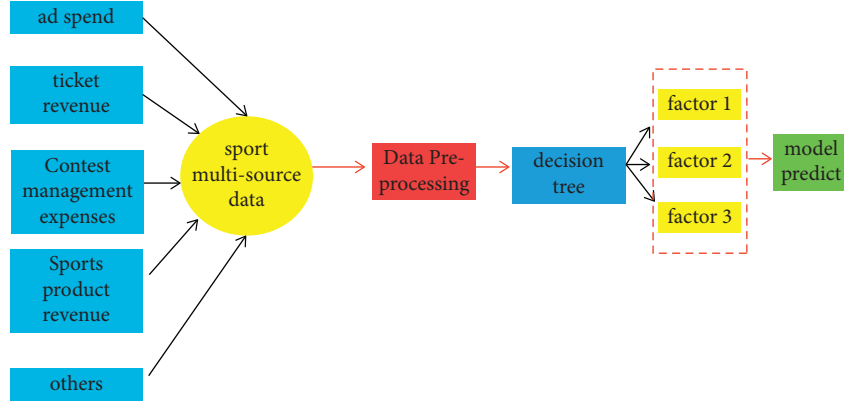


FIGURE 1: The process of multisource data classification and prediction of sports economic industry.

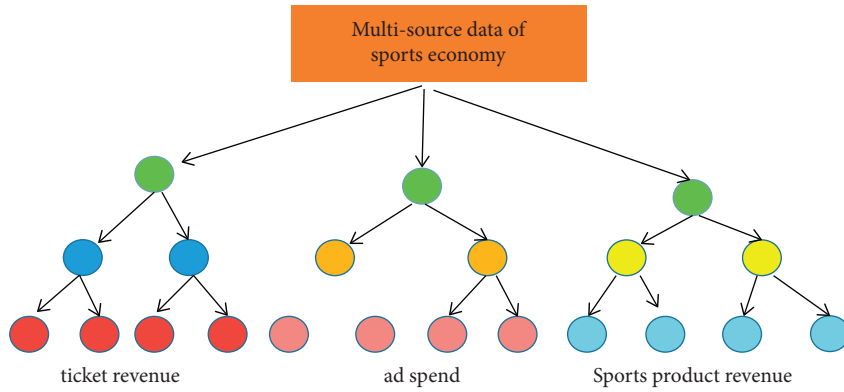


FIGURE 2: The schematic diagram of insurance data classification effect through clustering method.

In the classification task of the actual decision tree, conditional entropy is the most widely used evaluation index. This is because the classification task is not only affected by one factor but also needs to consider the influence of other classification factors. Equation (2) shows the calculation rule of conditional entropy. Conditional entropy can reflect the uncertainty of classification from another perspective, which can better guide the decision tree to complete the classification task.

$$H\left(\frac{D}{A}\right) = \sum_{j=1}^n \frac{|C_j|}{|D|} H(D_j). \quad (2)$$

Information gain represents the degree to which feature A reduces the uncertainty of dataset D , which is an evaluation index for reducing uncertainty. In the classification task, there are often many factors, which show the influence ability of feature A in the entire classification task. Equation (3) shows the calculation rule for information gain.

$$g_r(D, A) = \frac{g(D, A)}{H_A(D)}. \quad (3)$$

The Gini index is also an important indicator for decision tree tasks and is an important indicator for multiclass classification tasks. Equation (4) shows the calculation rules for the Gini index.

$$\text{Gini}(D) = 1 - \sum_{l=1}^L \left(\frac{|C_k|}{|D|} \right)^2. \quad (4)$$

3.3. A Neural Network Algorithm for Multisource Data Prediction in Sports Economic Industry. Neural network methods have obvious advantages in dealing with nonlinear, high-dimensional data. CNN can extract the feature relationship between sports economy very well, and LSTM can process time series very well. In this study, it is mainly used to extract the features of sports economy, and it does not involve time series. Therefore, CNN is chosen as the neural network algorithm for sports economic forecasting. It can efficiently map input and output data through weight and bias optimization. No matter how complex the relationship between input and output is, it always produces a valid mapping [31]. There are many kinds of neural network methods, whether it is dealing with image features or speech recognition features. They have different advantages and disadvantages in dealing with spatial features, temporal features, and environmental features, respectively. In this study, the convolutional neural network was selected to map the nonlinear relationship between multisource data of sports economic industry. Figure 3 shows the workflow of the convolutional neural network in processing multisource data relationships in the sports economic industry. These

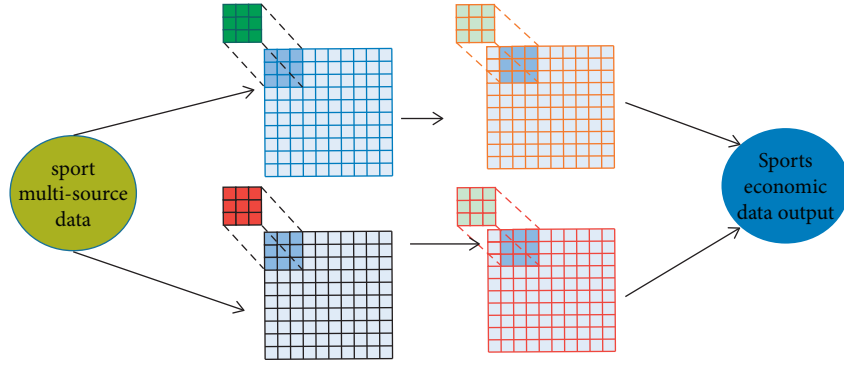


FIGURE 3: The neural network method in the process of multisource data mapping in sports economy.

multisource data are derived from the output data of the classification algorithm of the decision tree. These data will go through the convolution layer, pooling layer, and activation function of the convolutional neural network in turn and finally complete the mapping relationship between the input data and the output data. The hyperparameters of CNN mainly include the number of filters, the number of network layers, and the step size. The number of filters chosen in this study is 64. The number of CNN network layers is set to 4. The stride is chosen to be 1.

There are many hyperparameters involved in the calculation process of the convolutional neural network, such as the number of filters, the step size of the pooling layer, and the padding step size. Equation (5) shows the calculation relationship between these hyperparameters. This computational relationship will facilitate the hyperparameter finding process.

$$w' = \frac{(w + 2p - k)}{s} + 1. \quad (5)$$

The input form of the convolutional neural network is also a key step. Equation (6) shows the calculation relationship of the input of each layer of the convolutional neural network.

$$V = \text{conv2}(W, X, \text{"valid"}) + b. \quad (6)$$

Equation (7) shows the output form of the sports economic multisource data after passing through the convolutional neural network.

$$Y = \psi(V). \quad (7)$$

The neural network method involves many derivation operations, and equations (8) and (9) show the calculation rules for the derivation of biases and weights.

$$\Delta\omega_{ji} = -\eta \frac{\partial E}{\partial \omega_{ji}}. \quad (8)$$

$$\Delta u_{ij} = -\eta \frac{\partial E}{\partial u_{ij}}. \quad (9)$$

Equation (10) shows the convolutional operation of CNN, which is the main operation of CNN.

$$\delta_j^\zeta = \beta_j^{\zeta+1} (f'(u)_i^\zeta \text{up}(\delta_j^{\zeta+1})). \quad (10)$$

In order to reduce the computational load of the neural cell, CNN uses the pooled layer to carry out the downsampling. Equation (11) shows the computational process of the downsampling.

$$x_j = f\left(\sum_{u,v} \beta_j^\zeta \text{down}(x_i^{\zeta-1}) + b_j^\zeta\right). \quad (11)$$

Neural network methods involve two processes, forward propagation and backpropagation, which is where gradient descent comes from, and this process involves the propagation of errors. Equation (12) shows the error calculation rules for convolutional neural networks.

$$\begin{aligned} E &= \frac{1}{2} \sum_{k=1}^m [d_k - f(\text{net } w_k)]^2 = \frac{1}{2} \sum_{k=1}^m \left[d_k - f\left(\sum_{j=0}^n \omega_{jk} y_j\right) \right]^2 \\ &= \frac{1}{2} \sum_{k=1}^m \left[d_k - f\left[\left(\sum_{j=0}^n \omega_{jk} f\left(\sum_{i=0}^q u_{ij} \chi_i\right)\right)\right] \right]^2. \end{aligned} \quad (12)$$

3.4. The Processing of Multisource Data of Sports Economy. This study selects the relevant data of a football club in Beijing as the source of the dataset. The dataset mainly includes data on the sale of sports tickets, advertising expenditures, and the profitability of related products. For any data mining algorithm, the processing of the dataset is an important step, because the quality of the dataset directly determines the accuracy of classification or regression. The choice of hyperparameters is only to further improve the classification or prediction error, and it does not determine the trend of accuracy. Datasets often play a decisive role in an algorithm, which directly determines the effectiveness and accuracy of the algorithm. There are great differences in the multisource data of the sports economic industry, because different industrial companies and even different sports economic characteristics will have great differences. The data preprocessing operation process is particularly important for the classification and prediction of

multisource data in the sports economic industry. In this study, multisource data are processed into data that conform to the normal distribution, which will be beneficial to the accuracy of the algorithm.

4. Result Analysis and Discussion

The feasibility and accuracy of data mining methods and neural network methods are analyzed and discussed in this section. Other factors, such as sports advertising expenditure, ticket income, and sports product income, are the multisource data sources of this study. There are certain differences and similarities in the five factors of sports economy at the time of collection. If these data are directly input into the neural network, this will cause the phenomenon that the labels do not correspond to the input data one-to-one, so these data need to be classified. First, the decision tree method is used to classify these multisource data of the sports economy. The accuracy of the decision tree will affect the accuracy of the neural network method in the field of sports economic prediction. Figure 4 shows the classification error of the decision tree method for multisource data of the sports economy. It is obvious that the decision tree method is feasible in the classification task of the sports economy. All the classification errors are within 2.54% for the five key multisource data affecting the sports industry. The largest classification error is only 2.54%, and this part of the error mainly comes from the advertising expenditure of the sports industry. This is because the cost of advertising expenditure is greatly affected by the form of economic development and the national support rate. These factors are difficult to control for sports industry companies, and this influencing factor is closely related to the variability of time. The marketing error of sports products is only 1.14%. This part of the error is extremely small for the classification of the sports economy. This is because the marketing of sports products is related to the decision-making of company managers and the purchasing power of the people. This part of the error is small. It is less affected by time and market changes.

In order to more intuitively demonstrate the accuracy of the neural network method in the prediction of sports economic multisource data, this study selected 30 sets of data for different sports economic factors. Figure 5 shows the marketing state prediction error for sports products. It can be seen from Figure 5 that the marketing forecast value of sports products is in good agreement with the changing trend and data size of the actual data value. Only some data have large peak prediction errors, which may be due to the fact that this part of the error comes from the marketing of valuable sports products, and these sports products have relatively large variability. Overall, the neural network method has high reliability in predicting the marketing status of sports products.

Advertising spend (ad) has a large classification error, and Figure 6 shows the accuracy of the neural network approach in predicting advertising spend. Although the sports advertisement expenditure has a big error in the classification aspect compared with other sports economic

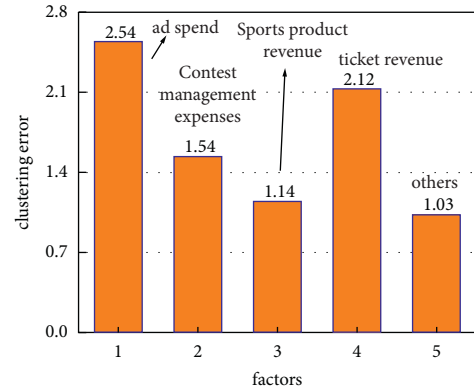


FIGURE 4: The classification error of multisource data in sports economy by a decision tree.

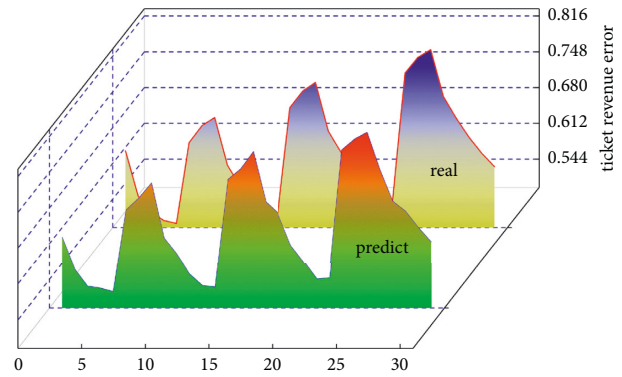


FIGURE 5: The predicted value and the actual data value of sports product marketing status.

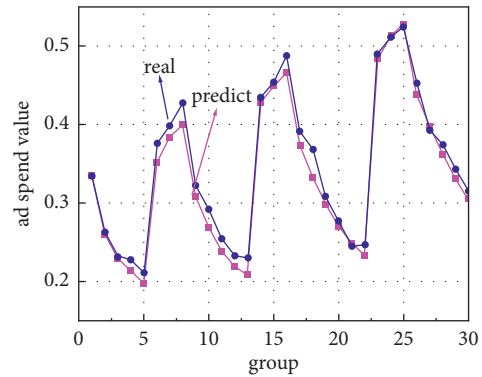


FIGURE 6: The comparison of the forecast value and actual expenditure data of sports advertising expenditure.

influence factors, the sports advertisement expenditure expense forecast aspect accuracy is higher. Through Figure 6, it can be seen that the forecast value of the expenditure of more than 30 groups of sports advertising is in good agreement with the actual expenditure, and only a small part of the data has a big error with the actual expenditure of advertising, but the margin of error is within acceptable limits. This part of the larger error may be due to the policy and time factors. So it is necessary to collect more datasets of advertising expenditure in time to train the model and

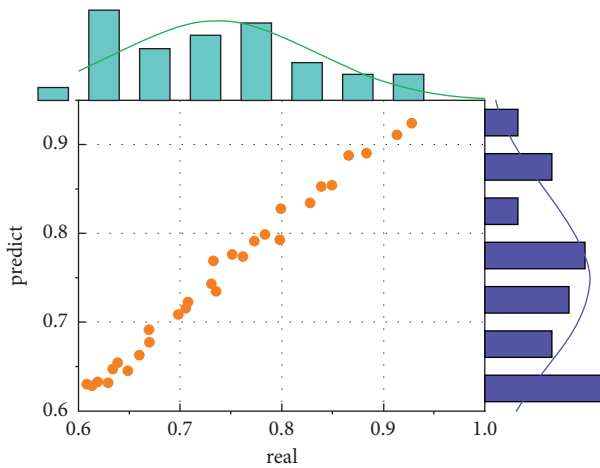


FIGURE 7: The curved distribution of predicted and actual sports ticket receipts.

improve the forecast accuracy of sports advertising expenditure.

For sports economy, the income from sports tickets is also an important source of data. Figure 7 shows the predicted value of sports ticket revenue through a neural network approach. In Figure 7, the upper part of Figure 7 represents the predicted distribution curve of sports ticket revenue, and the right part represents the actual distribution curve of sports ticket revenue. Through the linear independence line of Figure 7, we can see that the neural network method has a good correlation with the sports ticket revenue forecast, the correlation coefficient can exceed 0.95, and the forecast data value is basically distributed near the linear function. From the predicted normal distribution curve of sports ticket revenue, it can be seen that the neural network method can better predict sports ticket revenue, because the predicted normal distribution curve of sports ticket revenue has a similar distribution trends to the normal distribution curve of actual ticket revenue. From the state diagram data and distribution in Figure 7, the predicted value of sports ticket revenue is also in good agreement with the actual ticket revenue.

Figure 8 shows the error distribution of the five sports economic factors selected in this study. It can be seen from Figure 8 that the prediction errors of the five influencing factors are all within 3.2%, which is an acceptable range for the prediction of sports economy. Overall, the prediction error for the sports economic factor is larger than the classification error because this part of the dataset is larger compared to the classification of decision trees. The biggest source of error was 3.2%, which was also due to the cost of sports advertising. The income error of sports products is only 1.23%, which is favorable to the development trend of sports industry companies. It can be seen from Figure 8 that the prediction errors of ticket revenue and contest management are only 2.92% and 1.79%, which is also a relatively small error for sports economic management. Figure 9 shows the distribution curve of the influencing factors of the sports economy. It can be seen that the correlation between the predicted and the actual value of the influencing

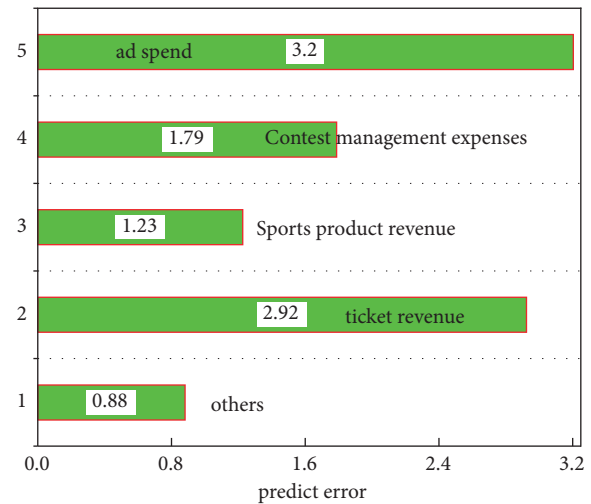


FIGURE 8: The prediction errors of sports economic influencing factors by the neural network method.

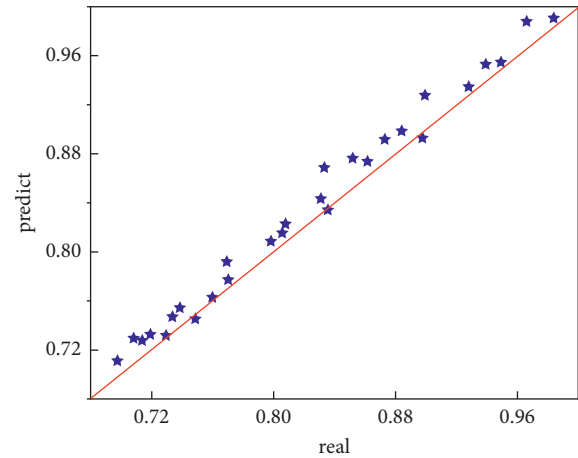


FIGURE 9: Linear correlation plot of sports economic forecast values.

factors of the sports economy is relatively high, the correlation coefficient basically reaches 0.97, and this is a very high correlation coefficient value. This also reflects the feasibility of the neural network method in the prediction of sports economic factors.

5. Conclusions

In recent years, China's comprehensive strength has rapidly developed, which has derived many forms of industrial models. The sports economic industry is also a relatively popular industry; it is a global economic industry. The development of sports economy can not only drive the rapid development of the national economy but also improve the health of the people. At the same time, with the continuous development of economic globalization, the economy has become a global economic activity. The development process of the sports economic industry is bound to produce many influencing factors, which will affect the development of the sports industry and the future development trend. How to

balance the relationship between these influencing factors is a more important task for sports companies. However, if only managers or professionals are used to manually process these complex data, it will not only affect the efficiency but also consume a lot of human and material resources. Data mining technology has demonstrated powerful data mining functions in many fields, which can assist people to discover much potential research object information. This study uses data mining methods and neural network methods to classify and predict the multisource data of the sports economic industry. The largest classification error is 2.54%, which comes from the classification of sports advertising expenditures. Likewise, the largest forecast error is 3.2%, which is also derived from the forecast of sports ad. This is because the expenditure of advertising expenses has a greater relationship with time factors and policy factors, and this part is relatively variable, but this error is also within an acceptable range for the sports economic industry. The classification and prediction errors of other industries affecting the sports economy are relatively small, and the minimum error is only 0.88%. The neural network method also shows good performance for the prediction of the advertising expenditure part and the revenue factor of sport-related products, and both the data value and the development trend are in good agreement with the actual data. The linear correlation coefficient of the predicted value of sports economic influencing factors also reached 0.97, which further demonstrated the feasibility and robustness of the data mining method and the neural network method in the prediction and classification of sports economic multisource data.

Data Availability

The 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 known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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