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Retraction

Retracted: Sports Risk Analysis Based on Knowledge Discovery and Data Driven

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] J. Zheng and C. Fan, "Sports Risk Analysis Based on Knowledge Discovery and Data Driven," *Security and Communication Networks*, vol. 2022, Article ID 8589200, 9 pages, 2022.

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Research Article

Sports Risk Analysis Based on Knowledge Discovery and Data Driven

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Sports have gradually gained popularity, and the risks associated with them have risen as well. In today's world, college students are a diverse population, and sports are very popular among them. The construction of sports risk assessment system in ordinary colleges is significant to improve physical quality of college students and ensure safety. College sports accidents have occurred on occasion in recent years, causing not only enormous pain to students and parents, but also casting a dark shadow over the sport. This work takes the risk analysis of college students' sports as the background, and uses a data-driven neural network to conduct knowledge discovery of college sports threats. It evaluates the sports risks of college students' physical education, and builds an index system of sports risk assessment in ordinary colleges and universities, which provides a certain basis for avoiding and reducing sports risks. This work studies an end-to-end one-dimensional convolutional neural network algorithm for risk assessment of college sports. In order to extract complementary structures in different scales, a multi-scale fusion framework is constructed using convolution kernels of diverse sizes. In this paper, the residual network structure is introduced to deepen and improve the network, and an attention module suitable for one-dimensional residual network is designed. It is embedded into the residual module to construct a multi-scale attention residual network (MSAR) model. Finally, validity and superiority of proposed model are verified by experimental data, which can effectively evaluate the sports risk of college students.

1. Introduction

The reform of higher education has continued to deepen, and the talent training model of colleges and universities has also been continuously adjusted. A major part of reforming higher education is creating college students who are well-rounded in all parts of their development-physically, emotionally, psychologically, morally, and sociallyl-to meet the society's need for college students. College and university sports programs must meet the minimum requirements set forth by the Ministry of Education, and these standards serve as a foundation for the ministry's review and inspection of college and university sports programs. There has been a fixed increase in the number of colleges and universities, as well as an increase in the number of college students, in recent years, as a result of the rapid expansion of education [1–5].

Compared with primary and secondary school sports, college sports are more confrontational, competitive and collective. In addition, the pressure of employment in today's society is increasing. College sports have clear goals and high exercise intensity. Some students with poor physical fitness are not suitable for high-intensity and long-lasting sports. In this way, various accidents are prone to occur in the process of specific sports, and even lead to the tragedy of sudden death of students. And sports come with their own set of risks, which means that accidents in college sports are unavoidable. Sports injury incidents have a significant impact on students' academic, psychological, and physical health, as well as casting a shadow on physical education instruction. At the same time, this has caused huge teaching pressure to the school and affected the normal teaching order. With the frequent occurrence of sports injury accidents in colleges, some colleges have to take a series of measures to reduce the occurrence of injury accidents, such as reducing the intensity of sports activities and reducing the opening hours of sports venues. Although the implementation of these measures can reduce the frequency of injury accidents, it also affects improvement of college students' physical quality as well as skill level, and reduces the enthusiasm of college students for physical exercise. In this way, college sports will gradually lose its original role, deviate from the original spirit, and also violate the original intention of school sports [6–10].

And with the development of today's era, once a sports injury accident occurs, if the school's handling results cannot be approved by the school or its parents, it is easy for the students or their parents to sue the court for a judgment. In the case that neither party is at fault, the court usually uses the principle of fair liability to deal with the legal liability of the injury accident, and the school will always bear a certain responsibility, which invisibly increases the financial pressure of the school. According to statistics, there are many abnormal deaths of college students every year. Students injured in sports and games have ranked first in student injury accidents and ranked third in court cases. Therefore, how to prevent and control the risk of college sports have become key issues to be solved urgently. Strengthening and improving the research for risk assessment for college sports is not only a theoretical hotspot, but also an urgent practical task [11–15].

It is important to ensure safe operation for physical education teaching in colleges as well as universities to use scientific and reasonable methods to assess the risks of sports in ordinary colleges and universities. Today's scholars mainly build an evaluation system from perspective of the risk of a certain sport in college sports, but seldom try to build a complete physical education teaching risk evaluation index system. And when assessing the risk of college sports, the method used is relatively backward. This work proposes a data-driven neural network for knowledge discovery of sports risk to improve the performance of sports risk assessment for college students.

The implementation of these measures can minimize the number of injury accidents; it also has an impact on the physical quality and skill level of college students, as well as their enthusiasm for physical activity. College sports will progressively lose their original role, depart from their original spirit, and contradict the original intent of school sports in this way. It ensures that students are safe while participating in sports, supports the orderly growth of sports in colleges, and prevents or lowers the occurrence of accidental accidents. This study uses a data-driven neural network to undertake knowledge discovery of college sports dangers, with the risk analysis of college students' sports as the backdrop.

The paper arrangements are as follows: Section 2 discusses the related work of college sports. Section 3 introduces the various methods for using the convolutional neural network. Section 4 collects the different college sports data and analyzes the experiments. Section 5 concludes the paper.

2. Related Work

In the literature [16], risk management is based on the investigation, prediction, gathering and analysis of risk elements such as the uncertainty and possible risk. Determine how to detect and measure risks, manage risks, and dispose of losses produced by risks in a methodical and scientific manner. Literature [17] believes that risk management in school physical education organization refers to the combination of modern risk management theory and the characteristics of physical education organization. Drawing on the risk analysis and solutions in process for school physical education teaching organization, management method of school physical education teaching organization is put forward. Literature [18] believes that some sports with physical confrontation, such as basketball and football, have the highest probability of sports injury accidents. The majority of sports injury incidents occur in junior high schools, and the majority of the causes are due to the school's management's negligence. Sports injuries are caused by the inherent hazards that come with participating in sports. External variables that contribute to sports injury accidents include uneven terrain, damage to facilities, a lack of instructor accountability, a faulty school safety system, and a lack of students' self-protection skills. Literature [19] believes that the main reasons affecting campus sports safety are students' physical quality, sports venues, teachers' sports safety awareness, class organization, and sports venue equipment supervision, and the scientific and organized school management. Literature [20] believes that the risk of sports activities for high school students can be roughly divided into physical fitness-oriented risks and skill-oriented risks according to the classification of projects. The main factors affecting risk cognition mainly include students' own physiological and psychological characteristics, such as students' personality, and the object factors affecting risk cognition mainly include sports venues and inadequate management of equipment. Literature [21] believes that the organizational risks in sports activities mainly come from both inside and outside the classroom, and the organizational risks of physical education mainly come from the environment, venues and equipment, and teachers' teaching. The risks of extracurricular sports activities mainly come from the masses and self-organized sports training. Substantial recommendations for these risks are then given. Literature [22] believes that the main reasons for sports risks in colleges and universities are students' physical conditions, school safety system, students' sports safety skills, students' and teachers' sports safety awareness, and the safety of sports equipment.

Literature [23] believes that three levels of indicators can be established to assess swimming safety risks. Primary indicators include people, environment and management systems. The second-level indicators are refined on the basis of the first-level indicators. The human aspect includes lifeguards and tourists, the environmental aspect includes the natural environment and site environment, and the management aspect includes the management of people and objects. The third-level indicators are further refined.

Literature [24] believes that the main reasons for the risk of small ball projects include human aspects, environmental aspects, and management aspects. Teachers' lack of sports safety understanding, students' inattentiveness, inappropriate dress, and other human factors are all part of the human factor. Sports venues, damaged equipment, elderly age, and other environmental factors are all factors to consider. School management and teacher self-management are two components of management. Inadequate supervision of physical education classes and concealed threats in management are examples of school management. Negligence in teacher management and poor intensity control are examples of teachers' self-management. Literature [25] believes that the evaluation system of primary and secondary schools can construct 5 first-level indicators. They are from the school side, the teacher side and the student side. In addition, there are secondary indicators, such as establishing evaluation standards, supervising work, formulating prevention and control measures for sports risks, and strengthening students' and teachers' awareness of sports safety. Literature [26] believes that the indicators for evaluating the risk of sports activities include the degree of harm, the possibility of occurrence, the consequences of loss, the observability, and the controllability.

Literature [27] believes that the methods to deal with risks mainly are: risk retention, risk reduction and other methods. Literature [28] believes that the sports risks of amateur sports training in Shanghai are mainly artificial risks. Training institutions can purchase insurance for athletes to transfer risks. Compared with other insurances, the premiums are very low and cannot fully provide protection for athletes. Therefore, the risk management of the risk of amateur training sports should start with the prevention of risks, the treatment of risks and the protection of risks. Literature [29] believes that the main reason for the failure of long-term management of school sports is that the school sports safety system is not perfect and the basic guarantee for accident handling is not enough. In order to cope with these, measures such as strengthening the top-level design, reducing the burden on schools, purchasing insurance for teachers and students, and expanding the channels for school risk transfer can be adopted. Literature [30] believes that the processes to reduce the occurrence of risks mainly contain enhancing people's risk awareness, strengthening the ability of relevant management agencies to manage risks, and purchasing insurance for risk transfer.

3. Method

Here, discusses the procedures of deep learning and convolutional neural network. The CNN offers a lot of strength when it comes to extracting feature information and fitting models. They define the residual network.

3.1. Convolution Neural Network. Algorithms for deep learning such as CNN are widely used. Convolutional, pooling, and fully connected layers make up the major structural components of CNN, a feedforward multi-layer neural network model. To achieve feature learning, convolution and pooling generally take place in the network's convolution and pooling layers. A fully connected layer is then used to disseminate the collected feature maps to further layers, where they are merged with a Softmax function layer to get the classification results.

Each convolutional layer typically contains numerous convolution kernels, each of which performs a specific convolution operation on a specific section of the input signal or feature map. The global feature map is created by connecting the local features to the higher-level network. Additionally, each convolution kernel must traverse the output of the previous layer, and the weight parameters of any convolution kernel in this process remain unchanged. Convolutional layer parameters can be reduced by weight sharing, reducing computational requirements for training models and avoiding overfitting. The calculation criteria are

$$X_j^l = f\left(\sum X_i^{l-1} * w_{ij}^l + b_j^l\right). \quad (1)$$

It is possible to achieve a nonlinear mapping of the input features of the convolutional layer through the activation function, and thus increases linear separability of the data by translating features from the original multi-dimensional space to another space. The nonlinear activation function in neural networks is

$$\begin{aligned} \sigma(x) &= \frac{1}{(1+\exp(-x))}, \\ \tanh(x) &= \frac{(\exp(x)-\exp(-x))}{(\exp(x)+\exp(-x))}, \\ \mathrm{ReLU}(x) &= \max(0, x). \end{aligned} \quad (2)$$

Because of the sigmoid function's inability to produce a zero-mean output, non-zero-mean signals will accumulate in the pre-network and slow down convergence. The tanh function overcomes the zero-mean problematic, but like the sigmoid function, it has the same problems of gradient disappearance and exponentiation. When the absolute value of the input data is large, the derivatives of both functions tend to be zero. This makes the gradient disappear after the error passes through the multi-layer network during the back-propagation process, resulting in slow or even stagnant update of the weight value. The ReLU function has many advantages such as low computational complexity, unilateral inhibition, wider excitation boundaries, and sparse activation.

Pooling layers are commonly seen between convolutional layers in the structure of convolutional neural nets. In order to reduce the number of parameters and calculations in the network and control over-fitting, it is used to perform down-sampling operations on the feature map and reduce the feature map one at a time. Max and average pooling are two of the most commonly used pooling functions. It is possible to use either a maximum or an average pooling method, in which case the maximum activation value in the local receptive field will serve as an output value.

The neurons in the fully connected layer have complete connections with all neurons in the previous layer, which are used to integrate the discriminative local feature information between different categories. In the convolutional neural network model, the output of the previous layer of network is spread and connected to realize the mapping from the feature to the sample label space, which constitutes the input of the fully connected layer. Then, with the processing of the hidden layer and softmax function, the classification result is achieved.

By reducing the transmission of internal variables during network training, the batch normalization layer is able to speed up network training while also improving network model stability and generalization performance. Batch normalization is applied between each convolution layer and the activation layer in the convolutional neural network model suggested in this chapter. For each training session, the BN layer separates the convolutional layer's input by its standard deviation, minus the min-mean batches. As a result, the input value distribution is normalized to a conventional normal distribution, which speeds up model training. However, just normalizing the input to the network layer will confine the input to a linear range, limiting the network's expressiveness. Therefore, the scale and offset are introduced into the normalization process to scale and move the normalized values, thereby restoring the expressiveness of the network layer.

3.2. Multi-Scale 1D Convolutional Neural Network. Convolutional neural networks offer a lot of strength when it comes to extracting feature information and fitting models. The convolutional layer, activation layer, and pooling layer of CNN each process the input data. As the number of feature channels grows, the size of the feature map shrinks. Simultaneously, the feature information extracted by various sizes of convolution kernels differs. As a result, combining features extracted from different convolution kernel sizes can increase CNN's feature expression capabilities at several levels. To actualize the complementarity of information at multiple scales, a multi-scale fusion architecture is built using convolution kernels of various sizes. Convolution kernels of various sizes make up each layer of the multi-scale framework. A convolutional layer with a convolution kernel size of 321, as well as a pooling layer with a size of 21, make up the first section of the network model structure that is used to extract short-term information from the original vibration analysis. This feature map is then passed into a multi-scale framework.

3.3. Residual Network. As the number of neural network layers continues to deepen, the network will become difficult to train, and the training accuracy of the network will reach saturation, resulting in network degradation. The ResNet structure solves this difficulty by stacking numerous residual modules that use a shortcut connection to implement the network layer's identity mapping. The residual module fits a residual map rather than a straight map of stacking numerous network layers. Assuming that the input of a residual module is X, denoting the direct mapping as $H(x)$, the corresponding direct mapping can be redefined as $H(x) = F(x) + x$. Fitting a residual map to the network is much easier than fitting a direct map. It can be done using shortcut connections, in which the higher layer's input X is connected to one or more layers of networks. The shortcut connection just performs identity mapping and adds its output to the residual block's output. The structure of a residual module is shown in Figure 1.

3.4. Attention Mechanism. The generation of attention mechanism is closely related to the working mechanism of human visual attention. As visual information processing system tailored to humans. It enables people to get the focus from the information to be processed with only limited attentional resources. In this way, more important details can be quickly obtained, while the interference of other irrelevant information is shielded. This section will introduce the Squeeze and Excitation Networks (SENet) and the Convolutional Block Attention Module (CBAM) of the attention module used in the proposed model in detail. And reconstruct the attention module structure suitable for one-dimensional convolutional neural network model according to its algorithm flow.

SENet explicitly models dynamic, nonlinear interdependencies between feature channels by introducing a Squeeze and Excitation Module. This simplifies the learning process and improves the quality of output features and the expressiveness of the network. The SE module suppresses useless and redundant features by automatically learning the weight distribution of each feature channel, and then enhancing important features according to the channel weights. The schematic diagram of SE module is shown in Figure 2.

The convolutional channel relations built by the SE module have global and local properties. After a series of conventional convolution and pooling operations, a feature map with feature channel C is obtained, and then the SE module re-calibrates the feature map through squeezing and excitation operations.

3.4.1. Squeeze Operation. Since the convolution kernel only uses the values within the local receptive field to participate in the operation, each computing unit that transforms the output will ignore other contextual information. Therefore, the global average pooling operation is used to compress the global spatial information of each channel, and a set of channel weight values are obtained to describe the channel information. The calculation process of the c-Th feature of z can be expressed as

$$z_c = F_{sq}(u_c). \tag{3}$$

3.4.2. Excitation Operation. Through this operation, the channel aggregation information obtained in the previous step can be used to obtain the complete correlation between channels. Therefore, the excitation operation must first be flexible and able to learn the nonlinear relationship between

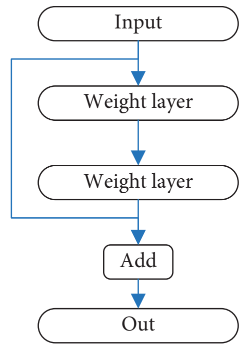

Figure 1: Residual learning structure diagram.

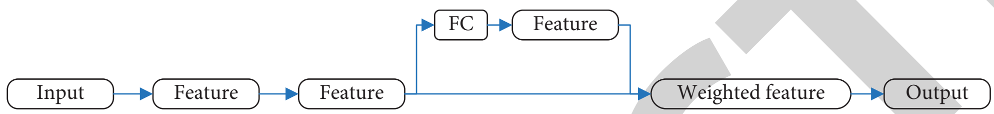

Figure 2: Schematic diagram of SE module structure.

channels. The second is to be able to learn non-mutually exclusive relationships, thus ensuring that multi-channel incentives can be achieved. The ReLU function is used as the activation function in a basic sigmoid gating mechanism to meet the aforementioned requirements during the excitation operation. The following is an expression for the gating mechanism:

$$s = F_{ex}(z, W). \tag{4}$$

In order to limit the complexity of the model and increase the versatility, two fully connected layers are added before and after the ReLU function to form a bottleneck structure to realize the parameterization of the gating mechanism. To maintain a consistent channel size, run the output through the dimensionality reduction layer with a dimensionality reduction ratio of r, then through the ReLU activation function, and finally through the dimensionality raising layer to convert the output to $H \times W \times C \times U$. The Sigmoid function is used to scale the result of the excitation operation to get the normalised feature channel weights. The output of the excitation operation is the weight distribution of the feature channels, which in turn multiplies the corresponding feature channels, and finally obtains the recalibrated attention feature map. At present, mainstream neural networks are constructed by repeatedly stacking unit modules, so SE modules can be easily embedded into existing network models.

The Convolutional Block Attention Module (CBAM) is a lightweight general module. It can be easily embedded into the existing mainstream convolutional neural network structure, and the extra computation added is negligible. The main purpose of the CBAM and SE modules is the same, and their difference is that CBAM uses both maximum pooling and average pooling. And it generates weights through the information of two dimensions of feature channel and space, and realizes the re-calibration operation of the original feature. The structure of CBAM is illustrated in Figure 3.

CBAM consists of two attention modules, channel and space. Similar to the SE module, when using channel correlation to calculate channel attention, it is also necessary to squeeze the given feature map first. Then, both average pooling and max pooling are used to aggregate the spatial information of the feature maps to obtain finer channel attention. The feature map generates two different spatial context descriptors after two pooling operations, and the two descriptors are passed to the shared network. Then its outputs are summed element-wise to generate channel attention feature weights.

The spatial attention module is primarily utilized as a supplement to the channel attention module to get the spatial location of significant features and to realise the description of the spatial correlation between features. When calculating the spatial attention feature map, it is first necessary to aggregate the channel information of the feature map along the axis of the feature channel through the max pooling and average pooling operations to generate two sets of feature descriptors. They represent the max-pooled feature and average-pooled feature of the feature channel, respectively. The two feature maps are then concatenated and passed through a standard convolutional layer to generate a spatial attention feature map, which encodes the spatial location of reinforcement or suppression.

3.5. Multi-Scale Attention ResNet. The first part of the multi-scale attention ResNet (MSAR) consists of a convolutional layer and a pooling layer. The short-term features in the original data are extracted through 64 large-size 32×1 convolution kernels, and the input feature map of the multi-scale residual module is obtained. Three groups of residual modules and attention modules make up each layer of the multi-scale residual attention module. Each residual module has two convolutional layers that are identical. The attention module is connected after each residual module to adjust the weight distribution of the feature response and increase the expressive ability of the feature. The attention module will

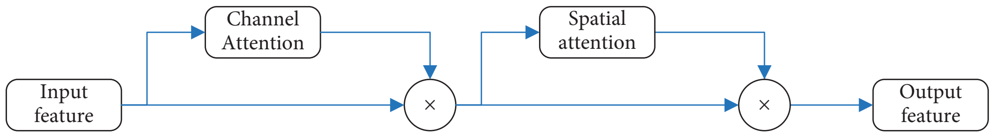

Figure 3: CBAM module overall structure diagram.

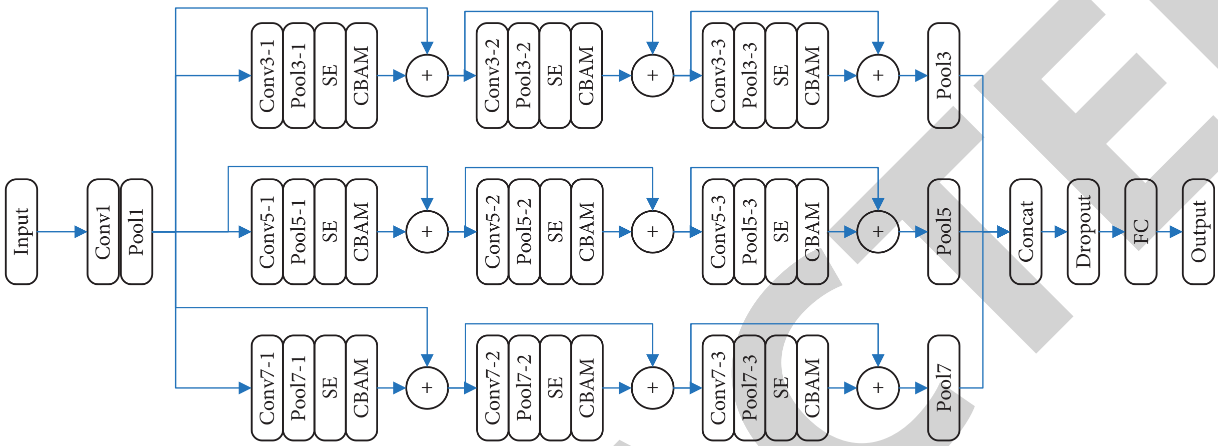

Figure 4: MSAR model structure diagram.

use the SE module and the CBAM module. The features of each convolutional layer are fused by a function. Finally, pass the features to the fully connected layer and softmax to output the classification result. The structure of MSAR is illustrated in Figure 4.

4. Experiment

In this section, collect the different sports college data and analyze the experiment. Then estimate the network performance. They are discussing the network loss by the training process.

4.1. Dataset. This work collects a series of college sports risk data by itself, which is used to train the network and evaluate the network performance. The dataset contains 35013 training examples, with half of the training samples being test samples. Each sample is characterized by 12 college sports risk indicators, and the specific information is shown in Table 1. The label of each sample is the corresponding exercise risk level, which is divided into 5 levels. This paper uses precision and F1 score as performance metrics for network evaluation.

Table 1: The information of college sports risk index.

Number	Index
y1	Rules and regulations
y2	Hardware facilities
y3	Duty of care
y4	Professional obligation
y5	Safety consciousness
y6	Operational behavior
y7	Knowledge reserve
y8	Physical fitness
y9	Motor behavior
y10	Natural environment
y11	Teaching venue
y12	Teaching equipment

4.2. Network Loss. In a neural network, the training process of the network is a very important link, and whether the network can converge is the basis for subsequent network testing. In order to estimate the training process of the network, this work statistically analyzes the loss during the network training process. The experimental results are illustrated in Figure 5.

Obviously, as the number of iterations grows in the early stages of training, the network loss lowers dramatically. The network's loss effectively stops dropping when the training period reaches 60, indicating that the network has achieved a point of convergence. This shows that the MSAR network designed in this paper is correct and feasible in the overall design.

4.3. Comparison with Other Evaluation Methods. To further verify the effectiveness of the network proposed in this work, it is compared with other risk assessment methods for college sports. The comparison methods involved are BP-based, RBF-based and CNN-based, and the experimental results are illustrated in Table 2.

Compared with other evaluation methods, the MSAR method proposed in this work can achieve the best performance: 95.2% precision and 93.1% F1 score. Compared with the best performing CNN-based methods in the table, 2.7% precision improvement and 1.6% F1 score improvement can be obtained. This verifies the validity and correctness of this work.

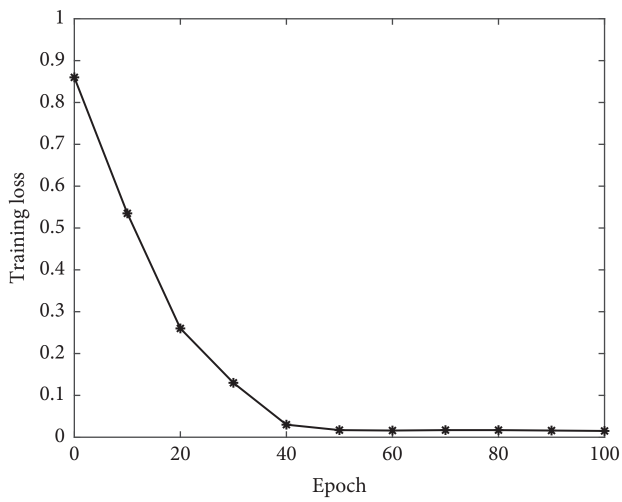

FIGURE 5: The training loss.

TABLE 2: Comparison with other evaluation methods.

Method	Precision	$F1$ score
BP-based	87.90	85.21
RBF-based	90.31	87.60
CNN-based	92.54	91.49
MSAR	95.20	93.10

4.4. Experimental Results of Multi-Scale Features. As mentioned earlier, this work uses convolutional filters of different scales to perform feature extraction on the data at different scales. To verify the effectiveness of this strategy, this work conducts comparative experiments to compare the network evaluation performance using single-scale features and multi-scale features, respectively. The experimental results are illustrated in Figure 6.

It is obvious that the best evaluation performance can be obtained using multi-scale features. Compared with single-scale features, the evaluation network for multi-scale features can obtain 2.6% precision improvement and 1.6% F1 score improvement. This verifies the validity and correctness of this work using multi-scale features.

4.5. Experimental Results of Attention. As previously stated, this research employs an attention mechanism in an MSAR network that combines SE and CBAM. To verify the effectiveness of this strategy, this work conducts comparative experiments to compare the evaluation performance with and without the attention mechanism, respectively. The experimental results are illustrated in Figure 7.

It is self-evident that the best evaluation results are produced by paying attention to SE and CBAM. MSAR can enhance precision by 2.3 percent and F1 score by 2.0 percent when compared to not employing attention. This verifies the correctness of combining SE and CBAM in this work, which can facilitate the network to extract more discriminative features.

4.6. Experimental Results of Dropout. As mentioned above, this work uses the dropout strategy to optimize the network

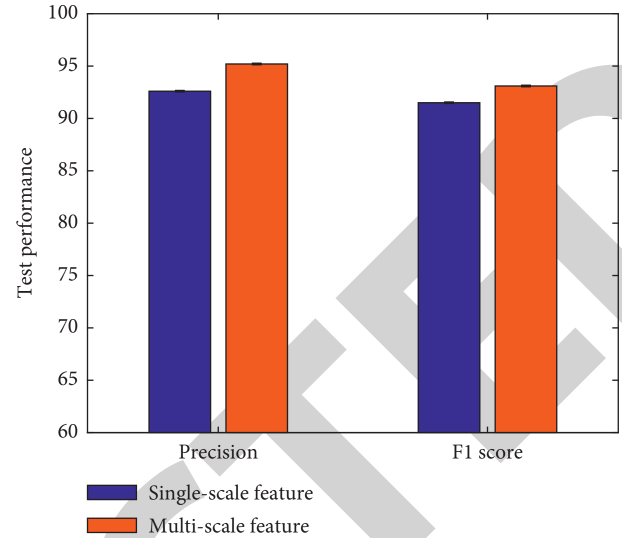

FIGURE 6: Experimental results of multi-scale features.

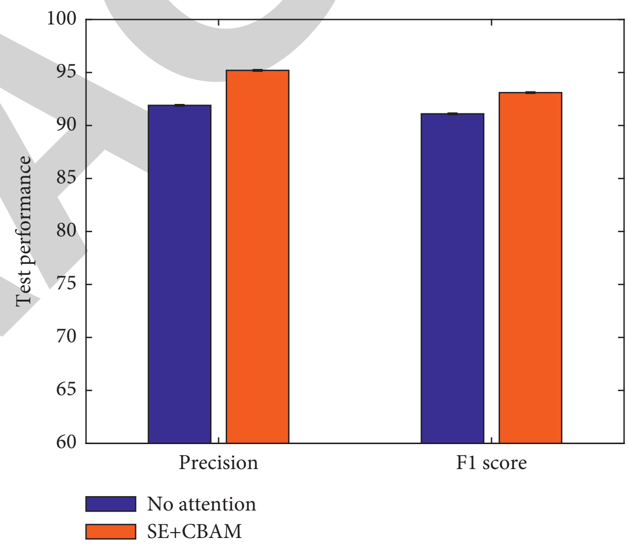

FIGURE 7: Experimental results of attention.

TABLE 3: Experimental results of dropout.

Method	Precision	$F1$ score
No dropout	93.90	91.70
Have dropout	95.22	93.11

and alleviate the overfitting phenomenon of the network. To verify the effectiveness and correctness of this strategy, this work conducts comparative experiments to compare the network performance with and without dropout, respectively. The experimental results are illustrated in Table 3.

It is obvious that the best evaluation performance is obtained using dropout. Compared to not using dropout strategy, MSAR can get 1.3% precision improvement and 1.4% F1 scores improvement. This verifies the correctness of dropout in this work.

5. Conclusion

Based on research on sports risk in colleges, this project seeks fresh views and entrance ways. It examines risk elements in the college sports process and adds to and improves the risk assessment index system for college sports. This allows schools and universities to dig deep into their internal investigations of teachers and students using their systems, and sort out the elements that could lead to sports-related dangers at colleges and universities. Then take effective measures based on these indicators to reduce the risk value. It provides a safe sports environment for students, promotes the orderly development of sports in colleges, and avoids or reduces occurrence for accidental injuries. This work takes the risk analysis of college students' sports as the background, and uses a data-driven neural network to conduct knowledge discovery of college sports risks. This work investigates an end-to-end automated and intelligent risk assessment based on convolutional neural networks, which addresses the problems of complex processes, reliance on expert knowledge, and insufficient learning ability of shallow structure features in traditional sports risk assessment methods. In this paper, a multi-scale one-dimensional convolutional neural network model is proposed, and the model is further improved through residual network and attention mechanism. The residual module is used to build a multi-scale feature fusion framework and an overall network structure to improve the efficiency and accuracy of network recognition. This work introduces two attention modules, SE and CBAM, and embeds them into the residual module, and proposes a multi-scale residual network model based on attention mechanism for risk assessment of college sports. The experimental results demonstrate that the strategy proposed in this paper can improve exercise risk assessment performance. Furthermore, the findings of this article can be applied to the assessment of exercise risk in other groups.

Data Availability

The datasets used during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The author declares that he has no conflicts of interest.

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