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INTEGRATION OF ATHLETE TRAINING MONITORING INFORMATION BASED ON DEEP LEARNING

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Abstract. In order to solve the problem of mining and analyzing athlete training monitoring information, the author proposes a deep learning based integration of athlete training monitoring information. The author proposes a deep learning based method for integrating athlete training monitoring information, deploying agents on various data source nodes, collecting athlete training information from each data source, and implementing denoising and dimensionality reduction on the monitoring information; Building an information integration model based on convolutional neural networks in deep learning; Extracting monitoring information features through convolutional layers, and fusing information with similar features into the same category through output layer classifiers, completing the integration of athlete training volume monitoring information. The experimental results show that as the number of iterations increases, the classification accuracy of the integrated model based on convolutional neural networks is continuously improving, while the error is continuously decreasing and getting closer to zero. When the maximum iteration number is 100, the model accuracy is 99.74%. The average Gini coefficient of the author's research method is higher, indicating a higher integration accuracy of the method.

Key words: Deep learning, Convolutional neural networks, Training volume monitoring information, Pre-processing, Integration methods

1. Introduction. Information management integration is a scientific data and information management method that effectively collects, stores, and shares various information resources such as graphics, text, numbers, and videos to meet the information needs of relevant entities. The information involved is diverse. It can be classified and stored according to different types of information, processed according to business processes or decisions in the corresponding fields, and shared through the LAN or the Internet. It is closely related to people's daily life and work. Simply put, information management integration is a scientific management approach that optimizes and allocates information as a valuable resource, with strong planning, technical, and targeted capabilities. The integration of information management follows the basic principles of "scientific planning, unified leadership, comprehensive control, and effective organization". With the help of various application technologies such as cloud computing and the Internet of Things, a set of algorithms is set up to build corresponding information management systems, achieve reasonable flow diversion and effective integration of information, quickly filter junk information, extract effective information, and store it targeted for future value development and utilization [1,2].

High exercise load training may lead to an imbalance between stress and recovery, which in turn can cause symptoms such as overtraining, excessive fatigue, psychological exhaustion, and psychological fatigue. And these symptoms can cause many adverse consequences, such as decreased grades, suspension of training, and so on. Obviously, it is crucial for the system to monitor the training process of athletes and adjust their exercise load in a timely manner. Overtraining not only reduces the functional status of athletes and physical activity participants, but also damages their emotions and motivation to participate in activities. Severe overtraining can also lead to their withdrawal from the activities they engage in [3]. The best way to avoid overtraining is through systematic monitoring and effective prevention. The comprehensive evaluation of training effectiveness has always been a key and difficult issue in athlete training. By improving the weight of evaluation indicators, effective evaluation of all data can be achieved. Construct corresponding indicator and evaluation sets to

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facilitate the implementation of the evaluation model, and correct the original data by assigning different weight values to them. Use the double value coefficient of difference entropy and difference weight to correct and ensure the accuracy of training and evaluation [4]. Professional sports athletes need to undergo years and months of exercise to continuously enhance their physical functions in order to stand on the competitive stage. Due to the differences in individual physical fitness of athletes, there are also differences in training methods and amounts. In order to accurately determine whether the training volume meets the standard, it is necessary to monitor the athlete's training situation in real time, fully understand the athlete's physical condition, determine whether the training plan is reasonable, whether the training can enter the next stage, and whether the training method needs to be adjusted. In summary, monitoring athlete training volume information is crucial for athlete training effectiveness [5].

2. Literature Review. A good training motivation can enable athletes to fully participate in training, enabling them to complete the tasks of each training session with higher quality, and stimulating their desire to win and achieve good results, at the same time, coaches should also consider the physical condition of athletes when formulating training tasks. The training motivation corresponding to the different states of athletes at different times is different. Training motivation is the starting point of training courses. Coaches should pay close attention to the training information of athletes, scientifically formulate training plans, start from the dynamic changes of athletes, and grasp the correct methods to stimulate motivation, in this way, the athlete's state will soar during each training session, and the training motivation will be maintained. The correct application of training motivation can help athletes maintain a relatively stable psychological state during each training session, which plays an important role in the rhythm and cycle arrangement of training sessions. Reasonable use of sports motivation can make athletes more active and hardworking in completing training content during training sessions [6]. There are many studies related to information integration. Jing, Z. et al. proposed an intelligent system based on deep learning and machine learning methods to classify and diagnose electrocardiogram signals, in order to improve their classification and recognition accuracy. Improved the detection ability of martial arts athletes for arrhythmia diseases and obtained accurate diagnostic information for arrhythmia [7]. Sadler, J. M., and others explored the benefits of using multitasking deep learning to model two interdependent variables (daily average flow and daily average stream water temperature). The multi task scaling factor controls the relative contribution of auxiliary variable errors to the total loss during training [8]. Pan, S. et al. proposed a key pose extraction method for motion videos based on region of interest classification learning. By fine-tuning the convolutional neural network, a network model suitable for weight lifting video classification in regions of interest was obtained. Finally, based on the classification results, a selection strategy for the classification results was designed to extract key poses [9].

Based on these research experiences, the author proposes a deep learning based method for integrating athlete training monitoring information. Deploy the Agent to various data source nodes to collect athlete training information from each data source, and perform denoising and dimensionality reduction on the monitoring information. Using convolutional neural networks to construct an information integration model, extracting features of monitoring information through convolutional layers, and then using output layer classifiers to fuse information with similar features into the same category to complete the integration of athlete training monitoring information.

3. Method.

3.1. Integration of athlete training volume monitoring information. The types of athlete training monitoring information are diverse and stored in different data source systems. Therefore, the primary step in integrating monitoring information is the collection of these multi-source heterogeneous monitoring information, which is achieved through multiple Agent systems [10]. Deploy the Agent on various data source nodes of the monitoring system, collect information from each data source, and transmit the information to the central server through a transmission program for subsequent analysis. The specific process is shown in Figure 3.1.

The monitoring information of athlete training volume is ultimately integrated into the central server for further processing and analysis [11].

3.2. Pre processing of athlete training volume monitoring information. The training volume information of athletes has multi-source heterogeneity, and its form, attributes, dimensions, format, quality,

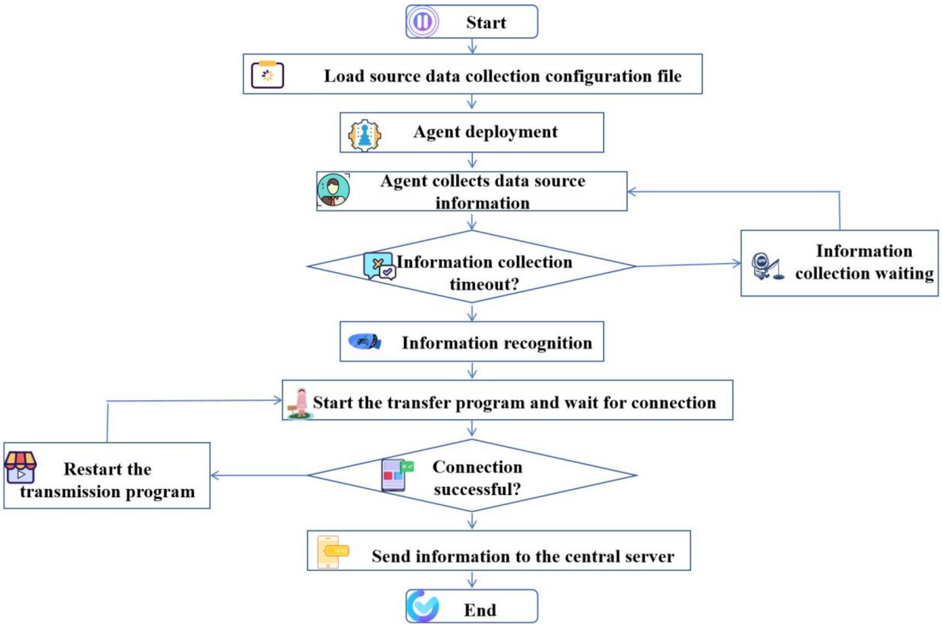


Fig. 3.1: Integration process of athlete training quantity monitoring information based on Agent

etc. do not meet the subsequent processing standards. Therefore, it is necessary to preprocess the training volume information of athletes, including denoising and dimensionality reduction.

3.2.1. Noise reduction. Due to the influence of monitoring and transmission equipment, there may be some noise in the monitored athlete training volume information. Therefore, it is necessary to remove this noise information and reduce noise interference. The information denoising process is as follows:

Step 1. Select a wavelet basis and perform wavelet decomposition on the monitoring information.

Step 2. Calculate the coefficients of each wavelet decomposition layer using the following formula:

$$k_{i,h} = \begin{cases} k_{i,h}, |k_{i,h}| \geqslant \zeta \\ 0, |k_{i,h}| < \zeta \end{cases} \tag{3.1}$$

In the formula, $k_{i,h}$ represents the wavelet decomposition coefficient, ζ represents the critical threshold. Threshold per layer ζ formula is as follows:

$$\zeta = e\sqrt{2\log_2 H} \tag{3.2}$$

Among them,

$$e = \frac{(median|k_{i,h}|)}{0.6745} \tag{3.3}$$

In the formula, e represents the standard deviation of noise estimation; $median|k_{i,h}|$ represents the intermediate value of each layer's wavelet coefficients; H represents the length of wavelet coefficients.

Step 3. Use the threshold function sign() to perform threshold quantization on $k_{i,h}$ and obtain $k'_{i,h}$.

$$k'_{i,h} = \begin{cases} sign(k_{i,h})(|k_{i,h} - \zeta|), |k_{i,h}| \geqslant \zeta \\ 0, |k_{i,h}| < \zeta \end{cases} \tag{3.4}$$

Step 4. Reconstruct $k'_{i,h}$ to obtain the denoised athlete training amount information.

3.2.2. Dimension reduction. Dimensionality reduction refers to reducing the dimensionality of information [12]. The role of dimensionality reduction is to reduce the unimportant parts of monitoring information. The PCA method based on mutual information comprehensive credibility is used for dimensionality reduction, and the specific process is as follows:

Step 1. Convert the athlete training amount information into matrix form, where Z_{nm}, n represents the information attributes, and m represents the number of information samples.

Step 2. Calculate the absolute mutual information credibility and relative mutual information credibility for Z_{nm}.

The calculation process of absolute mutual information credibility:

① Calculate the mutual information MI(ψ) of feature attribute ψ;

② Determine whether MI(ψ) is equal to 0. If it is equal to 0, the absolute mutual information credibility MC(ψ) of the feature attributes is 0; If it is not equal to 0, the formula for calculating MC(ψ) is as follows:

$$MC(\psi) = \frac{maxMI(\psi)}{MI(\psi)} \tag{3.5}$$

In the formula, $maxMI(\psi)$ represents the maximum mutual information value between each feature attribute and category D_i.

The calculation process of relative mutual information credibility:

a) Calculate other mutual information LMI(ψ) for feature attribute ψ.

b) Determine if LMI(ψ) is equal to 0. If not, the relative mutual information credibility $MR(\psi)$ of feature attribute ψ is:

$$MR(\psi) = \frac{maxMI(\psi)}{LMI(\psi)} \tag{3.6}$$

If it is equal to 0, proceed to the next step.

c) Determine whether max$MI(\psi)$ is equal to 0. If it is not equal to 0, $MR(\psi) = a$, a represents the comprehensive credibility threshold of mutual information; If it is equal to 0, $MR(\psi) = 0$.

Step 3. Calculate the comprehensive mutual information credibility $MS(\psi)$:

$$MS(\psi) = MC(\psi) + MR(\psi) \tag{3.7}$$

Step 4. Add ψ with $MS(\psi)$ greater than a to the new matrix.

Step 5. Use PCA method to reduce the dimensionality of matrix Y.

After the above denoising and dimensionality reduction, the quality of monitoring information has been greatly improved, making it easier for subsequent information integration [13,14].

3.3. Feature extraction and integration based on deep learning. There are various forms of deep learning network models, and convolutional networks are chosen here for feature extraction and integration of monitoring information. Convolutional neural networks are mainly composed of 5 layers, each responsible for handling different tasks.

① *Input layer.* The input layer is the input window for monitoring athlete training volume information.

② *Convolutional layers.* The convolutional layer extracts features from athlete training monitoring information through convolutional functions and obtains feature maps. The convolution function expression is as follows:

$$y_i = f(b_i + \sum_i T * x_i) \tag{3.8}$$

In the formula, y_i represents the i-th monitoring information feature output; x_i represents the i-th monitoring information sample of the input person; T is the convolutional kernel* Representing convolution operations; b_i is the output bias of the i-th monitoring information feature; $f()$ represents the activation function.

③ *Pooling layer.* The main function of pooling layers is to select the features extracted by convolutional layers, reduce the number of features to improve computational efficiency, and avoid overfitting in convolutional neural networks [15].

④ *Fully connected layer.* The role of fully connected layers in convolutional neural networks is to associate the features extracted by the convolutional layers together, achieving feature level fusion of monitoring information. The fusion formula is as follows:

$$u(x) = f(C_0 + E_0 x) \tag{3.9}$$

⑤ *Output layer.* The output layer contains many softmax classifiers, whose main function is to integrate information from similar features into the same category based on classification rules and fused features, completing the integration of athlete training volume monitoring information. The expression for the softmax classifier is as follows:

$$S = \begin{bmatrix} P(y_i = 1|x_i; \theta_1 u_1) \\ P(y_i = 2|x_i; \theta_2 u_2) \\ \vdots \\ P(y_i = K|x_i; \theta_K u_K) \end{bmatrix} \tag{3.10}$$

In the formula, S represents the final output result of the classifier; P represents the probability that an unknown monitoring information sample belongs to a certain category; y_i represents the category label of monitoring information samples; x_i represents the training set of the sample; θ represents the parameter vector in the classifier; K represents the number of sample categories; U represents the fusion features of each type of monitoring information sample.

Before performing feature extraction and integration, convolutional neural networks need to undergo a training process, which involves performing the above five levels of operations to obtain the classification integration results of the convolutional neural network, and then calculating the deviation between this result and the actual classification integration results. When the deviation exceeds the set acceptable value, the error needs to be backpropagated and the parameters of each layer of the convolutional neural network need to be updated until the deviation is less than the set acceptable value, completing the integration based on the convolutional neural network model.

3.4. Characteristics of Information Technology. Information is processed through information technology, and checklists are constructed for many electronic information, with different results. Compared to manual information processing in the past, this selection and management mode can access electronic information very accurately. Electronic information technology is an effective combination of hardware devices and information systems, which can batch process electronic information and further improve the efficiency of larger scale information processing. At the same time, enhance the research and development of hardware devices to further improve the speed of information systems. In the process of electronic information processing, electronic information technology is a collection of real life, and many of its information data depend on different industries. However, with the help of electronic information technology, various types of information can be processed and screened, and electronic information management systems can be used to better manage relevant information [16].

3.5. Strengthening Deep Learning and Information Integration. Today's information society has almost become a highly digitized society, with individuals engaged in a certain field of work or in daily life almost completely covered by various computer network technologies. The massive dissemination of information resources is no longer limited by various factors such as time, space, and distance. People can freely choose smart handheld communication devices such as smartphones and tablets to receive this massive amount of information anytime, anywhere, and conveniently. At the same time, in the process of rapid development and expansion of production capacity in industrial business models, the competition among global enterprises has become increasingly severe and intense. In the market environment, in order to quickly occupy some advantageous important positions, it is necessary to timely collect and accumulate market information, especially pay

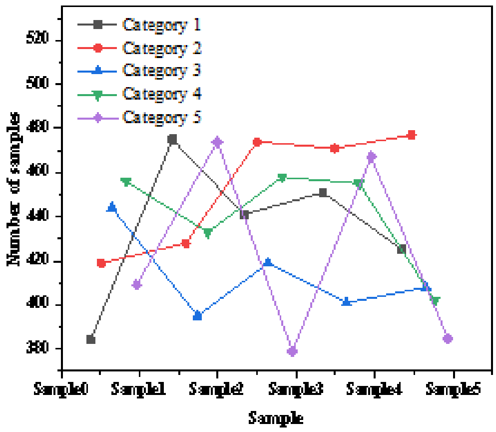


Fig. 4.1: Sample Distribution Map

Table 4.1: Convolutional Neural Network Model Parameter Settings

layer type	name	Variables and dimensions	Hyperparameter
0	Input layer	64×64information matrix Filter height: 6	Minimum batch size: 30
1	Convolutional Layer	Filter width: 6 Number of filter channels: 1 Filter width: 6 Filter count for each convolutional layer: 8	Learning rate: 0.05 Activation function: ReLU
2	Pooling layer	Bias: 0	Regularization weight decay rate: 0.02
3	Fully connected layer	80	Iteration count: 100 Activation function: ReLU
4	Output layer	6outputs	Training sample rate: 60

attention to the updating of talents and culture, the improvement of knowledge level, and the enhancement of enterprise management and operation awareness. Adequate and correct awareness and understanding of the importance of information technology. Therefore, enterprises can actively promote their information management knowledge system to employees, further enhancing their awareness of the integration and innovation of information management and information technology [17].

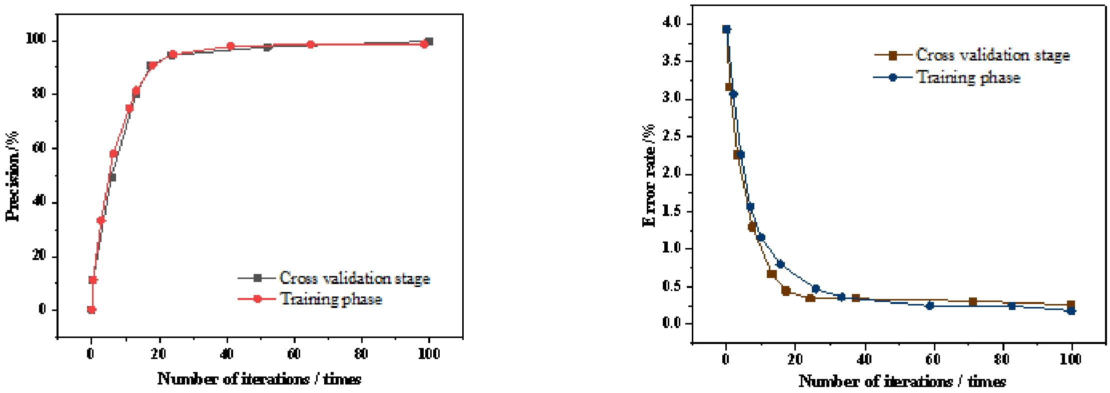
3.6. Simulation testing and analysis. In order to test the effectiveness of the integration method studied in athlete training volume monitoring information processing, a simulation test was conducted by comparing it with integration methods based on overlap, least squares, and hierarchical clustering [18].

4. Results and Discussion. There are a total of 5 samples of athlete training monitoring information used in the simulation test, and the specific situation of each sample is shown in Figure 4.1.

Construct an integrated model based on convolutional neural networks using the Simulink toolbox in MATLAB. The parameter settings related to this model are shown in Table 4.1.

The integrated model based on convolutional neural network was trained using training samples, and the results are shown in Figure 4.2.

From Figure 4.2, it can be seen that as the number of iterations increases, the classification accuracy of



(a) Comparison of model accuracy

(b) Comparison of model error rates

Fig. 4.2: Model Training Process

Table 4.2: Comparison of Precision of Integration Methods (Gini Coefficient)

Sample	Integration methods studied	Integration method based on overlap degree	Integration method based on least squares method	Integration method based on hierarchical clustering
1	84.14	78.14	82.14	77.14
2	86.11	77.10	83.20	76.21
3	85.03	76.25	84.14	75.10
4	83.13	75.14	81.55	76.25
5	85.25	76.21	82.47	77.76
Average Gini coefficient	84.731	76.567	82.707	76.501

the integrated model based on convolutional neural networks is continuously improving, while the error is continuously decreasing and getting closer to 0. When the maximum iteration number is 100, the accuracy of the model is 99.74%. At this point, a well-trained convolutional neural network-based integrated model is finally obtained, which can be used for subsequent testing and analysis [19,20].

The evaluation index of the integrated model is the Gini coefficient, and the calculation formula is:

$$Gini = 2 \times AUC - 1 \tag{4.1}$$

In the formula, the larger the Gini value, the better the model performs, and AUC represents the area enclosed by the coordinate axis under the classification ROC curve.

Under the same testing conditions, the test samples are classified and integrated using the methods studied, the integration method based on overlap, the integration method based on least squares, and the integration method based on hierarchical clustering. Then, the Gini coefficient is calculated based on the integration results. The results are shown in Table 4.2.

Comparing the Gini coefficients of the four integration methods mentioned above, it can be seen that the average Gini coefficient of the studied method is larger, indicating that the integration method performs better and has higher integration accuracy.

5. Conclusion. The author proposes a deep learning based integration method for athlete training monitoring information, which integrates athlete training monitoring information into a central server. The monitoring information is preprocessed on the central server to obtain denoised and dimensionality reduced athlete training information. Combined with deep learning theory, feature extraction and integration are performed on the processed information, and through simulation testing and analysis, the effectiveness of this method has been proven. However, the sample size selected in this study was relatively small and there was a certain gap with the actual situation. Therefore, in future research, it is necessary to increase the number of test samples to further improve the integration effect of athlete training monitoring information.

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