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Research and Analysis of Sport Medical Data Processing Algorithms Based on Deep Learning and Internet of Things

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ABSTRACT With the development of computer and information technology, more and more data and image information are generated in medical field. Sports medicine, as an important branch of medical cause, is responsible for ensuring national sports safety and rehabilitation after injury. How to use a large number of sports medical data and cases to accurately analyze and mine useful data and information has become an important research direction of sports medical data processing and mining. This paper will focus on the information mining and analysis of large sports medical data, focusing on the loss of training mode and the accuracy of convolution algorithm. In order to achieve effective prediction and risk assessment of sports medicine-related diseases, this paper starts with the improved convolutional neural network deep learning algorithm, and adopts the resampling algorithm with self-adjusting function, supplemented by tensor convolution self-coding algorithm. Ural network model assists multi-dimensional data analysis of sports medicine. Finally, in order to build an intelligent medical data platform for sports medicine, this paper innovatively proposes a cloud-based hardware-in-the-loop simulation model. Experiments show that this method provides reference and technical support for the realization of a real cloud-based fusion system.

INDEX TERMS Sport medicine, improved deep learning algorithm, sport medicine big data, tensor convolution self-coding deep learning algorithm, cloud-end fusion hardware-in-the-loop simulation model.

I. INTRODUCTION

The field of medical and health is the focus of global attention, and a large number of new technologies and research results are applied to it. With the rapid iterative development of information science and computer technology, a large number of data have been generated in the medical field, especially in sports medicine, which is related to the health of the whole people. The development and progress of sports medicine relies more and more on the analysis and research of these data [1]–[5]. Sports medical data is a kind of complex data with continuous development, multi-modality and multi-dimension, which contains a lot of information [6]. Convolutional neural network in-depth learning is an artificial intelligence algorithm which can process multi-dimensional data. It is an important means to study and mine the effective and key information in the large data of health care. At the same time, the development of Internet of Things technology also enables the large data of sports medicine to be stored and processed in real time, quickly and effectively [7]–[9]. But the traditional convolution neural network algorithm will lose training mode and the accuracy of algorithm when dealing with huge amount of sports medical data. Therefore, it is of great significance to improve the current data mining technology of sports medicine and build a virtual cloud-based fusion hardware-in-the-loop simulation platform for improving the effective prediction and risk assessment of sports medicine[10]–[13].

Based on the above problems, a large number of scholars and research institutions have carried out research and Exploration on sports medicine and in-depth learning, sports medicine and Internet of Things technology. In the aspect of deep learning and sports medicine, American scholar [14]–[16] proposed Batch regularization, which proposed that the corresponding model of diversified training data in the training process would change with the deepening of the training level. The consequence was that the difficulty and gradient instability of training would increase,

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and the conclusion of the diversified training data with the big data of sports medicine. Lv P [17], a Chinese scholar, has proposed a deep network algorithm, which can realize hundreds of levels of training structure, removes the whole connection level and integrates all functions into one module, so that it can achieve faster data. Speed of transmission; American scholar [18]–[20] has constructed "Sports Medical Data Record" based on convolution neural network, which can help improve the theory of clinical diagnosis of sports. In the same year, it proposed to construct and analyze the representation information of sports medical accidents through sparse matrix in-depth learning system, thus realizing the related hidden diseases. Figure 1 shows the core principle and technology corresponding to risk prediction, which also represents the inherent technology mode of combining convolutional neural network with large data of sports medicine to some extent. Mahajan R, Chen M C and Tareef A et al. have achieved some results in naming body recognition of traditional sports medicine based on deep neural network algorithm [21]–[23]. Experiments show that the corresponding recognition speed and accuracy exceed the CRF model and achieve a large number of text training; Haubruck P et al. proposed a general deep learning architecture to study large data of sports medicine, and focused on the introduction of the cyclic convolution neural network model, which realized the parsing of natural language and improved the performance of the system [24], [25]. The precise mining of large data in sports medicine is too complicated and the cost of the algorithm is too high, which is not conducive to popularization and application.

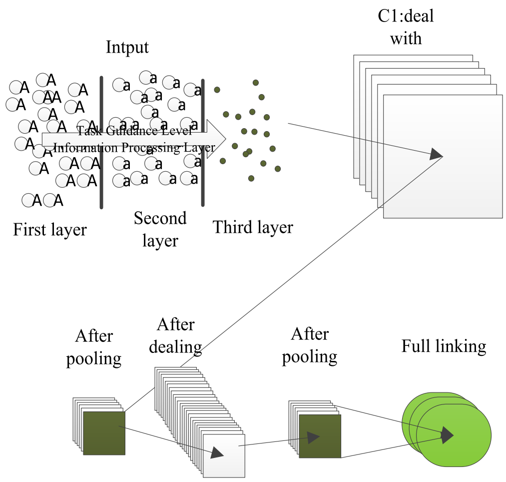

FIGURE 1. Network layer architecture of universal convolutional neural network.

In this paper, the deep learning algorithm and the large data of sports medicine are analyzed and studied. The main focus is to solve the defects of traditional deep learning algorithm in the model, so as to solve the problem that it is easy to lose the training mode. At the same time, this paper also proposes a cloud-end fusion semi-physical simulation model to be used for real cloud-end fusion. The system provides reference and technical support, so as to achieve accurate and effective mining of large data in sports medicine. In terms of technical details, in order to achieve effective prediction and risk assessment of sports medicine-related diseases, this paper starts from the deep learning algorithms, adopts the resampling algorithm with self-regulation function, and assists with tensor convolution self-coding neural network model to assist in the multi-dimensional data of sports medicine analysis.

This paper makes the following arrangements on the structure of the article:

Section II: The main work of this paper is to analyze the concept, algorithm core and existing problems of the deep learning convolution network which this paper relies on. At the same time, the existing problems of the current convolution neural network algorithm-based data mining in sports medicine are also analyzed.

Section III: Based on the analysis of Section 2, the core algorithm of the improved convolutional neural network is analyzed, and the resampling algorithm with self-regulation function is introduced. At the same time, this section will focus on the analysis of the auxiliary model tensor convolution self-coding neural network model, in order to achieve the analysis and processing of multi-dimensional data of sports medicine.

Section IV: In order to realize the construction of intelligent medical data platform for sports medicine, this section will design in detail and focus on the analysis and research of cloud-based fusion hardware-in-the-loop simulation model, so as to provide reference and technical support for the realization of real cloud-based fusion system.

Section V: This section will make a summary and outlook of the full text, and put forward the corresponding problems to be solved later.

II. APPLICATION AND ANALYSIS OF CONVOLUTIONAL NEURAL NETWORK ALGORITHMS IN SPORTS MEDICAL DATA

This section mainly lays the theoretical foundation for the third and fourth sections of the improved convolutional neural network algorithm and cloud-based fusion hardware-in-the-loop simulation model. The core algorithm of the convolutional neural network algorithm is mainly discussed and analyzed. At the same time, the research status and existing problems of the convolutional neural network algorithm when it is combined with large data of sports medicine are pointed out.

As an important part of deep learning algorithm, convolutional neural network algorithm has been applied in large data processing and image correlation processing more than traditional machine learning [26]–[28]. Convolutional neural network consists of five layers: input layer, convolution layer, pooling layer, full connection layer and transmission layer. The corresponding network structure is shown in Figure 2.

From Figure 2, we can see the operation process of convolution neural network in dealing with large data. First, the collected data passes through the convolution layer

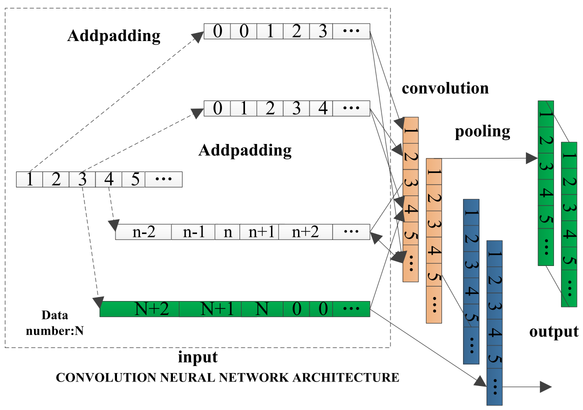

FIGURE 2. Structural chart of convolutional neural network algorithms in deep learning algorithms.

and the pooling layer of the whole system. These two layers extract the relevant features of the collected data and distribute them to the full connection layer and the classifier. The full connection layer acts on the classifier. A decision data is generated, in which such data is composed of probabilities. In the pooling layer stage, feature refinement and sub-sampling are the main features. The traditional neural network has about 1-3 layers in feature extraction layer, and the corresponding full connection layer is mainly realized by 3 layers of artificial network. After the above data processing, the corresponding processing results will be classified in the soft Max layer or directly processed by data regression.

III. ANALYSIS AND RESEARCH OF IMPROVED CONVOLUTIONAL NEURAL NETWORK ALGORITHMS

This section mainly studies the resampling algorithm with self-adjusting function, which is the key algorithm of the improved neural network proposed in this paper. At the same time, this section will study and analyze the auxiliary model tensor convolution self-coding neural network model. Finally, this section will propose the overall algorithm architecture of this paper.

A. STRUCTURAL HIERARCHY ANALYSIS OF CONVOLUTIONAL NEURAL NETWORKS

Convolutional neural networks correspond to the four structural layers corresponding to the combination of large data, which are described in detail as follows:

1) CONVOLUTIONAL LAYER

The convolution layer mainly contains the filter in the convolution neural network, which maintains a certain aspect ratio. For example, the first layer convolution of the conventional convolution neural network generally contains a convolution filter of about 5*5*3 size. In convolution layer, when forward propagation calculation is carried out, the filter needs to carry out conventional two-dimensional calculation on the input data, and in this calculation process, the point product of the convolution core and its corresponding input data part needs to be calculated. After a series of convolution operations, the output data will be reduced. At this time, there is almost no difference between the dimension of the output data and the content of the original data, but the corresponding data size will be reduced. The corresponding data calculation flow chart is shown in Figure 3.

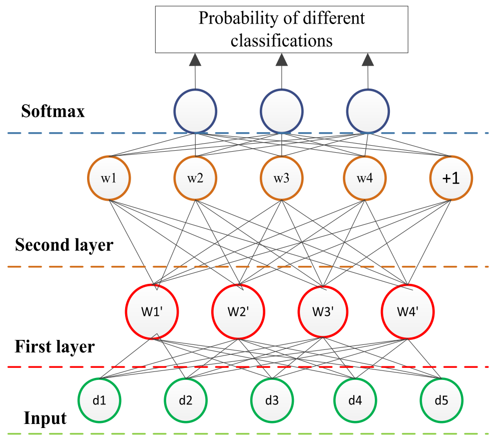

FIGURE 3. Data processing flow diagram of convolution part of convolution neural network.

In the actual training process of neural network, its essence is to iteratively update and learn the parameters in the convolution core of the convolution flow graph. The two most important characteristics of convolution layer are weight sharing and local connection. At the same time, in practical convolution calculation, it is necessary to specify a certain step size parameter. When the step size corresponds to 1, the corresponding convolution core only slides one pixel at a time, but when the step size equals 2 or even exceeds 2 to 3, its corresponding slip will only move 2 pixels at a time.

Taking the big data of sports medicine as an example, the details of the convolution layer processing the data text are as follows:

Assuming that the data amount of the input text of the large data of sports medicine corresponds to Formula 1, as follows. The corresponding j_n represents the coefficient vector in the S function.

$$SMSJ = (sj_1, sj_2, sj_3, sj_4, \ldots, sj_s) \tag{1}$$

The convolution result of each data in the corresponding *SMSJ* in Formula 1 above corresponds to $data(n)$. The convolution calculation of the corresponding n-th data is shown in Figure 4. If the corresponding convolution core is n and the corresponding window area is S_n, the convolution vector M of the corresponding M_n data can be expressed in Formula 2.

$$M_n^1 = wS_n + e^1 \tag{2}$$

The corresponding e^1 in formula 2 is deviation, and the corresponding w is the connection weight matrix between input layer and convolution layer.

2) POOLING LAYER

The Pooling layer mainly deals with the convolution vector M_n output from the convolution layer, in which the maximum

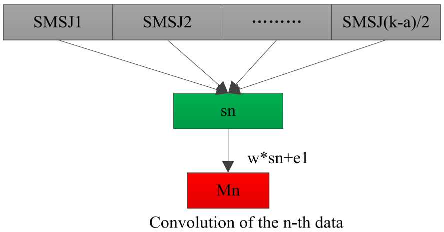

FIGURE 4. SJ convolution of the nth data in convolution layer.

value of n elements in the vector M_n can be expressed by formula 3 as follows:

$$M_n^1 = \tan M(M_n^1) \tag{3}$$

The operation of pooling layer in convolutional neural network system is divided into pooling operation and corresponding average pooling operation. The maximum pooling operation is usually used in large data processing of sports medical treatment. The main reason is that the data in large data of sports medical treatment are not exactly the same, and the corresponding data are complex and multimodal.

3) FULL CONNECTION LAYER

In the fully connected layer, an important structural layer behind the pooling layer, whose corresponding input is the output of the pooling layer, and the neurons between the corresponding two layers are connected by a fully connected way. The corresponding data processing expressions are shown in formula 4, where the corresponding m_n represents the output vector of the pool layer, the corresponding M represents the output value of the full connection layer, and the corresponding e and w represent the corresponding deviation.

$$m_n^1 = WM + E^4 \tag{4}$$

4) OUTPUT LAYER

The output layer mainly relies on the output of the soft maximum classifier to classify. When classifying, we need to select the corresponding classification function. There are two kinds of common classification functions, which correspond to sigmoid function shown in formula 5 and tanh function shown in formula 6.The corresponding e^x and e^{-x} in the formula represent the calculated parameters.

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{5}$$

$$f(x) = \frac{1}{1 + e^{-x}} \tag{6}$$

B. APPLICATION AND PROBLEMS OF CONVOLUTIONAL NEURAL NETWORK ALGORITHMS IN SPORTS MEDICAL DATA

When the traditional convolution neural network algorithm is used to process the large data of sports medicine, the corresponding data processing effect will be reduced when the large data of sports medicine is too large and the corresponding data set classification is not balanced. The application problems of convolution neural network algorithm combined with sports medical data are as follows:

1) THE TRADITIONAL CONVOLUTION NEURAL NETWORK SAMPLING HAS SOME PROBLEMS

It is only a simple data balanced sampling before training. The corresponding data sampling effect can not be guaranteed after the number of iteration training increases, and the corresponding accuracy of disease prediction will be greatly reduced.

2) LACK OF SYSTEMATIC INTELLIGENT MEDICAL DATA PLATFORM FOR SPORTS MEDICINE

Based on the above problems, the current research status is as follows: In the field of deep learning and sports medicine, American scholars put forward Batch regularization, which proposed that the corresponding model of diversified training data in the training process will change with the deepening of the level, and its consequences are that the difficulty and gradient instability of training will increase, and its combination with sports medicine data will also increase. It will lead to instability of disease prediction and misdiagnosis; Chinese scholar He Kevin and others have proposed deep network algorithm, which can realize hundreds of levels of training structure, remove the whole connection level, and integrate all functions into one module, thus it can achieve faster data transmission speed; American scholar has constructed a convolutional neural network based on the convolutional neural network. "Sports Medical Data Recording" can help improve the theory of clinical diagnosis of sports. In the same year, it proposed to construct and analyze the representational information of sports medical accidents through sparse matrix deep learning system, thus realizing the prediction of related hidden diseases and risks. Its corresponding core principles and techniques are shown in Figure 1 in section 1, which also represent the current convolutional nerves to some extent. The inherent technology mode of combining network with big data of sports medicine; Mahajan R, Chen M C and Tareef A et al. have achieved some achievements in naming body recognition of traditional sports medicine based on deep neural network algorithm [21]–[23]. Experiments show that their corresponding recognition speed and accuracy exceed the CRF model and achieve a large number of text training; Haubruck P et al. put forward a general deep learning architecture to study sports medicine data, especially the circular convolution neural network model, which realizes the parsing of natural language and improves the precise mining of large sports medical data, but the algorithm is too complex and the cost of the algorithm is too high, which is not conducive to popularization and application [24], [25].

C. ANALYSIS AND RESEARCH OF SELF-ADJUSTING RESAMPLING ALGORITHMS

In the research of traditional algorithm sampling algorithm, it is found that the corresponding data samples are unevenly distributed when the corresponding algorithm processes data. For example, the number of samples in one or some categories of corresponding data sets is much larger than that in other categories. The corresponding hierarchical model of traditional algorithm sample sampling is shown in Figure 5. The corresponding A, B and C in Figure 5 constitute the end-to-end training module. Each module is connected by the previous module. The resolution of corresponding module A is *128*128*3*, the resolution of corresponding module B is *256*256*3*, and the resolution of corresponding module C is *512*512*3*. The uneven distribution of modules in Figure 5 is called imbalance. If the corresponding modules are not trained directly without sampling, some classifications will not achieve good prediction ability. Based on this phenomenon, and considering the imbalance of data itself, this section proposes resampling to achieve sample equalization.

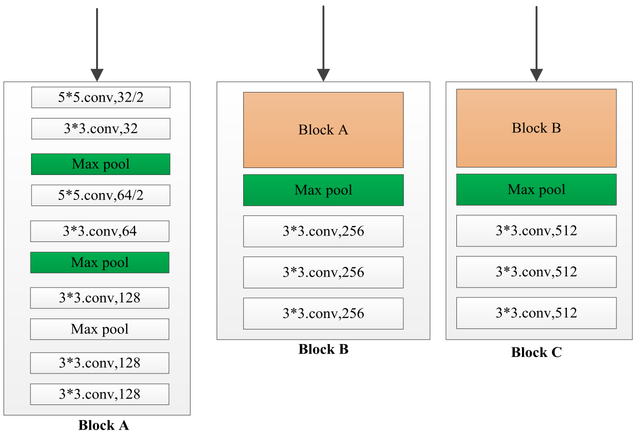

FIGURE 5. Hierarchical modular diagram of convolutional neural network.

The traditional data sampling mainly uses static sampling. The disadvantage of this method is that when there are too many types of tasks, the corresponding tasks differ greatly, and the corresponding undersampling and oversampling will have poor convergence effect. The main technical points of resampling proposed in this section based on this defect are as follows:

1) A SELF-ADJUSTING SAMPLING REALIZES DYNAMIC BALANCE OF DATA SET CATEGORIES, ACCELERATES CONVERGENCE AND REDUCES FITTING

By making full use of the dynamic adaptive strategy, the sampling has self-adjusting function and keeps it as close as possible to the distribution of the original data. The corresponding key data functions and command codes are shown in Figure 6 below.

The corresponding key formulas in the algorithm are shown in Formula 7.

$$w_1 = w_{init} \cdot \gamma^c + w_{final}(1 - \gamma^c) \tag{7}$$

Resampling of Self-regulation Function
1. Description of parameters
Balanced_weight: Initializes the class weight factor. For example: 1.36 = 1/73.63%.
Final_balanced_weight: The final category weight factor restores the original distribution.
Balanced_ratio: Balanced ratio, which gradually returns to the original distribution as iterations increase.
Count: Number of cycles.
Max_epoch: Maximum cycle.
Class - weight: Current weight factor.

2. Core algorithms:
```
Balaanced_weights: [1.36, 14.37, 6.63, 40.23, 49.6]    // / Initialize the weight factor.
Count: 0                                               // initialization iteration is 0.
While count < max_epoch
    Alpha: balanced_ratio//
    Class_weight: balanced_weight*alpha/final_balanced_weight
    Count: count + 1                                   // Next cycle
    Prepare_train_data (class_weight)                  // Initialize the data according to the weight factor.
    Train ()                                           // for the next round of training
End while
```

FIGURE 6. Resampling algorithm with self-adjusting function.

The corresponding w_1 is the current weight value in the code, the corresponding w_{init} is the initial weight balance value in the code, the corresponding w_{final} is the final weight of the current code, the corresponding y^c is the index parameter of the weight factor, and the corresponding c is the number of times.

2) REDUCE THE NUMBER OF DATA TRAINING AND EXPAND TRAINING DATA DYNAMICALLY

In order to solve the problem of minority class repeatability, this paper adopts random clipping technology to eliminate repeatability. Based on the corresponding module layer diagram of Figure 5, it is clipped. The corresponding clipping size is shown in Table 1.

Configure the style parameters based on Table 1, as shown in Table 2.

TABLE 1. Corresponding clip size.

Pre-edit Specification Dimensions	Post-edit dimensions
128*128	112*112
256*256	224*224
512*512	448*448

TABLE 2. Configuration style parameters.

style	parameter
Zoom_range	(1/1,1.1)
Rotation_range	(0,360)
Shear_range	(0,-1)
Translation_range	(-50,50)
Flip	No
Stretch	yes

Based on the above algorithm, the corresponding training process of the improved self-regulation function of the neural network is shown in Figure 7 below.

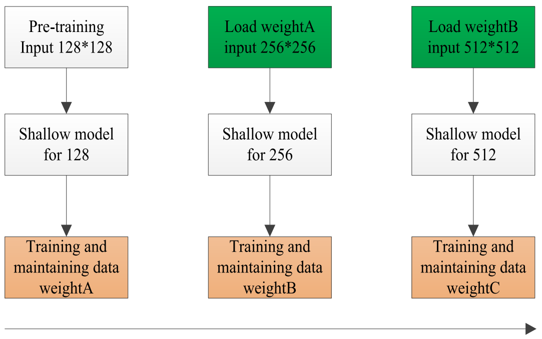

FIGURE 7. **Training data process of improved neural network self-adjusting resampling algorithm.**

D. ANALYSIS AND RESEARCH ON TENSOR CONVOLUTION SELF-CODING NEURAL NETWORK MODEL OF AUXILIARY MODEL

The auxiliary model tensor convolution self-coding is mainly the auxiliary model of the main model, which mainly realizes the processing and analysis of multi-dimensional data and improves the efficiency of processing and analysis. The tensor convolution self-coding neural network proposed in this paper mainly combines the structure of self-coding and convolution neural network, calculates the convolution layer output characteristic map, converts the convolution input data into one-dimensional vector, and carries out convolution operation to obtain the corresponding convolution results. The corresponding self-encoder is shown in Figure 8. Its main design steps are coding, reconstruction and updating parameters. Finally, the corresponding optimization objective function is obtained as shown in Formula 8, which mainly realizes the transformation of two-dimensional vectors into one-dimensional vectors.

$$J(\theta) = \sum_{i \in j} L(I, f'(f(I))) \tag{8}$$

The corresponding convolutional self-coding depth learning image feature schematic diagram is shown in Figure 9.

E. ALGORITHMIC ARCHITECTURE

Based on the above-mentioned self-tuning resampling algorithm and the corresponding convolutional self-coding deep learning model, this section will give the structure of the corresponding improved algorithm, as shown in Figure 10.

IV. DESIGN AND ANALYSIS OF CLOUD FUSION HARDWARE-IN-THE-LOOP SIMULATION MODEL

In order to further develop the platform of sports medical data processing, realize the requirement of intelligent sports health monitoring, and solve the problem of diversity and complexity of sports medical data types, this section will combine cloud system, big data technology and Internet of Things

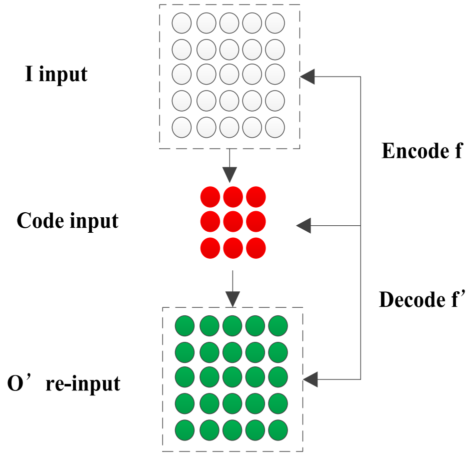

FIGURE 8. **Schematic diagram of self-encoder learning image features.**

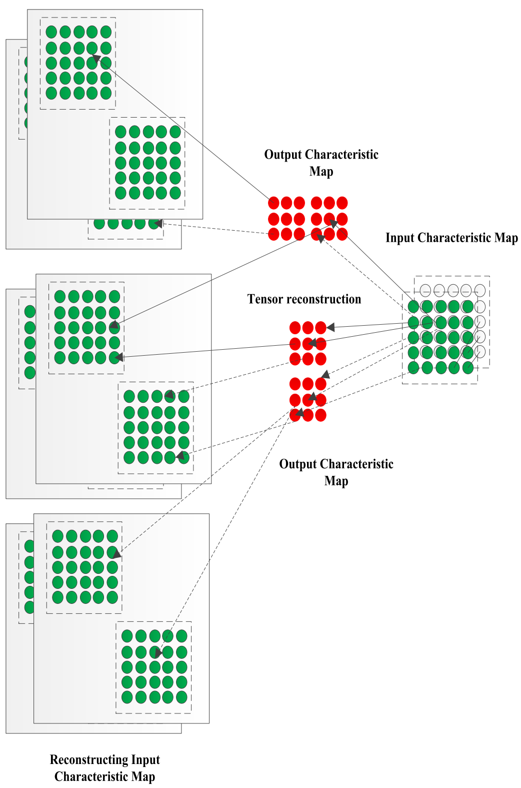

FIGURE 9. **Characteristic sketch of convolutional self-coding in-depth learning.**

technology to design the hardware-in-the-loop simulation model of cloud-based integration, and integrate the semi-real in cloud-based integration. In the physical simulation model, the improved deep learning algorithm is used as the data processing core.

A. DESIGN OF HARDWARE-IN-THE-LOOP SIMULATION MODEL FOR CLOUD FUSION

The structure of the cloud fusion system designed in this section is shown in Figure 11. The core of the

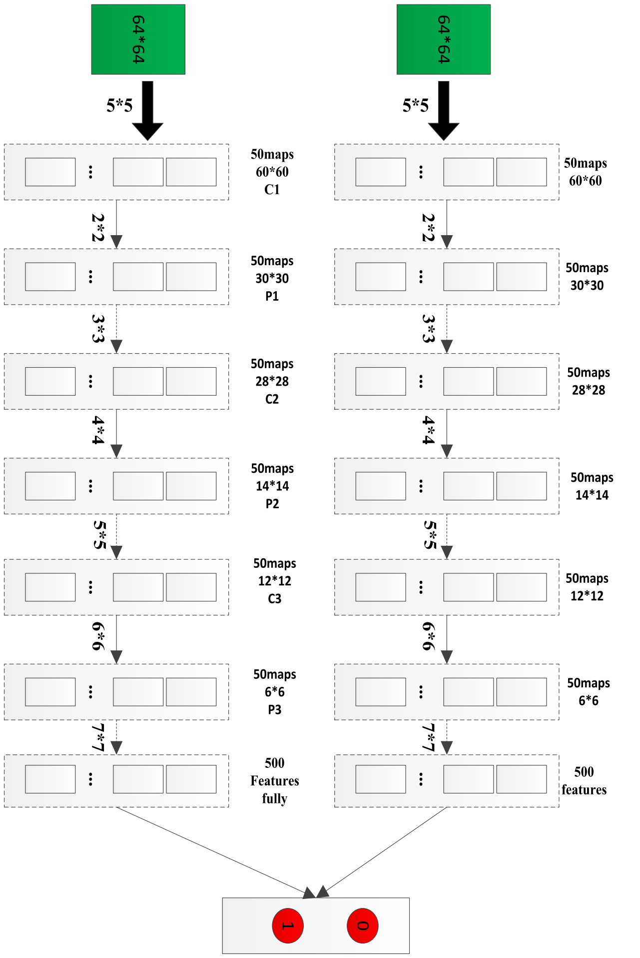

FIGURE 10. Structural diagram of improved convolutional neural network.

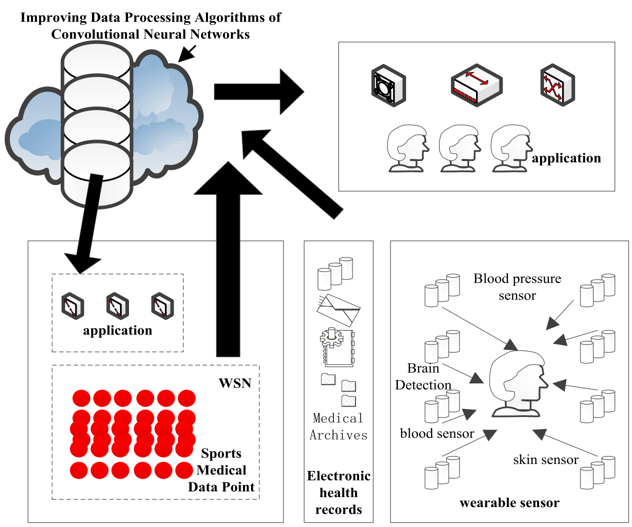

FIGURE 11. Hardware-in-the-loop simulation architecture proposed in this paper.

corresponding data processing center is the improved convolutional neural network algorithm proposed in this paper.

The corresponding components are as follows:

1) CENTRALIZED STORAGE OF DATA

In this model, the data collected by the corresponding physical layer will be filtered through the control layer and handed over to the cloud data center for storage and management.

2) UNIFIED API DATA INTERFACE DESIGN

Designing the established API interface to acquire the corresponding data does not require API interface to understand the physical layer, nor does it need to collect and process data.

3) SECURITY DESIGN

In the data security part, the cloud platform is mainly responsible for, this paper will centralize the data in a location that is easy to store.

4) CONVENIENCE DESIGN

In this layer design, all kinds of applications in the structure are unified into API interface.

In the design of network model, there are three levels: physical layer, application layer and control layer. The corresponding layer design is shown in Figure 12. In the physical layer, it contains sports health data including heartbeat, blood pressure and body temperature. In the corresponding control layer, it mainly connects the physical layer with the application layer. It mainly provides management services for physical devices with various functions and characteristics, and at the same time, it also provides services for the application layer. In the application layer, API is mainly developed and applied, which mainly includes sports health monitoring. The corresponding main working process is: selecting the appropriate sensor equipment and acquiring the corresponding sports medical data. The application layer obtains data from the cloud data center through the control layer. In the process of acquiring data, it first sends requests to the control layer, and at the same time sends the corresponding application data to the control layer. The control layer forwards the data to the corresponding application layer. At the data transmission level, the following three core formulas should be followed, such as the corresponding delay formula, network jitter formula and throughput formula shown in Formula 9, 10 and 11. Formula 9 corresponds to the delay formula, corresponding T represents the corresponding delay time, corresponding formula 10 corresponds to the network jitter formula RTT represents the jitter trace, corresponding $n$is the number of nodes, corresponding formula 11 is the throughput formula, where the corresponding Q value is the total value, and corresponding T value is the time.

$$\begin{cases} T = T_p + T_i + T_q \\ RTT = 2T \end{cases} \tag{9}$$

$$J = \frac{\sum_{i=2}^{\pi} RTT_i - RTT_{i-1}}{n-1} \tag{10}$$

$$B = \frac{Q}{T} \tag{11}$$

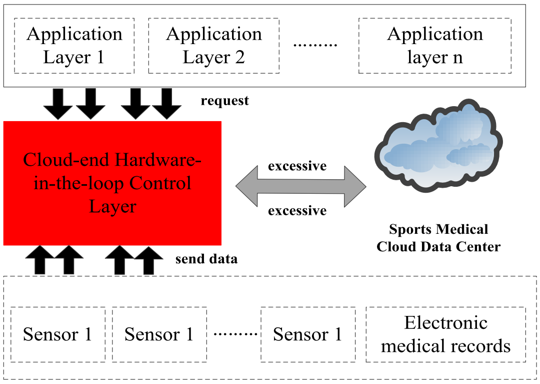

FIGURE 12. Network layer design diagram.

In this platform, the improved convolutional neural network proposed in the preceding chapters of this paper is used as the data processing core. The corresponding data training flow of the improved convolutional neural network is as follows:

Step 1: Configure data nodes and corresponding classification areas.

Step 2: Reduce the dimension of complex data and store it in the data storage area of network layer.

Step 3: Copy data and corresponding data models into different partitions through classification operations.

Step 4: The training nodes are booked on the convolutional neural network parameter server.

Step 5: When the training is preheated to a certain threshold, the latest data parameters are distributed to different classification areas.

Step 6: Start the training node to start training, set the delay mechanism to exchange data parameters.

Step 7: Training is assigned to the epoch deadline and the data parameter model is saved.

B. ANALYSIS OF HARDWARE-IN-THE-LOOP SIMULATION MODEL FOR SPORTS MEDICAL DATA TRANSMISSION

In order to verify the hardware-in-the-loop simulation model of sports medical data transmission, this section will carry out experimental processing, in which the medical data used are mainly sports medical data provided by a medical institution. The corresponding parameters are shown in table 3.Table 3 is the hardware parameters used in this paper.

Based on the database of injured parts and injuries of young volleyball players in a volleyball training camp, this paper analyses and studies the corresponding database based on the improved convolutional neural network data analysis algorithm. The statistics of injured parts are shown in Table 4 below. In the database of injuries in volleyball, this paper focuses on the analysis and judgment of injury grade corresponding to sampling contusion, joint sprain, waist and meniscus injury, and predicts the recovery cycle of athletes and the potential associated injury risk. After the analysis and judgment of the injury grade and the rehabilitation prevention report are completed, this paper assists doctors or athletes in the formulation of rehabilitation treatment plans based on such reports. The corresponding experiments based on the database are as follows:

TABLE 3. Technical parameters of hardware-in-the-loop simulation model platform (experimental conditions).

parameter	value
Network Area	412*412
Topological Model Structure	random
Number of total nodes	155
Data transmission rate in MAC layer	2.5Mbps
Transmitting Range of Sensor Nodes	65m
Number of hops from source node to gateway	5

TABLE 4. Statistical table of volleyball players'injury sites in a training camp.

Injuries	Number
Joint injury	33
contusion	59
Lumbar injury	21
ankle sprain	53
Lumbar muscle degeneration	29

Based on the above experimental conditions, the corresponding gateway delay breakdown diagram in the environment of Sports Health Internet of Things is shown in Figure 13(a). The file size transmitted is 600kB, the corresponding packet is 800B-1200B, the corresponding increment is 80B, and the transmission rate is set to 0.02s. Figure 13(b) shows the effect of transmission rate and packet size on average delay. It can be seen from the figure that when the transmission rate is set to 0.01s-0.06s, the corresponding increment is 0.01s.

Figure 14 shows the effect of different packet sizes and transmission rates on the maximum delay. It can be seen from the graph that the larger the corresponding data packet, the larger the corresponding delay, and the smallest corresponding maximum delay when the transmission rate corresponds to about 0.03s.

In terms of internal delay, the effects of different data sizes and transmission rates on internal delay are measured as shown in Table 5. From the table, it can be seen that different data packets and transmission rates have little effect on internal delay, which can be neglected.

To verify the corresponding total delay, as shown in Figure 15, the total delay of sport medical data transmitted from data source node to data center storage in the cloud-based hardware-in-the-loop simulation model is shown.

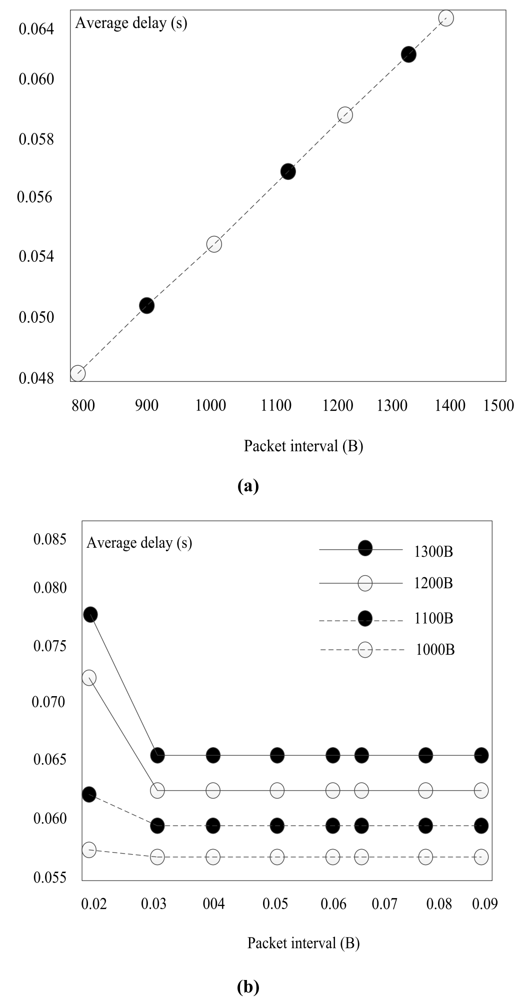

FIGURE 13. (a). Gateway delay breakdown diagram with 600 KB packet. (b). Gateway delay breakdown diagram with 600 KB packet.

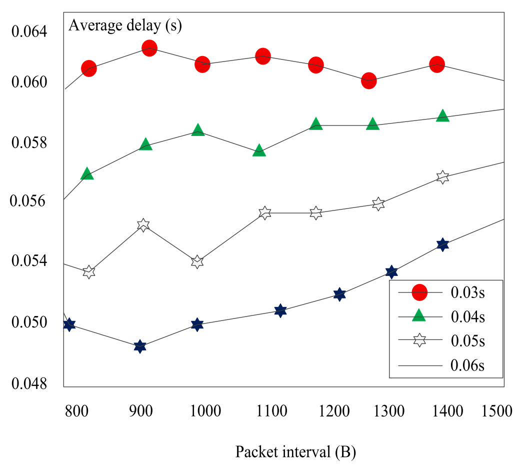

FIGURE 14. Effect of packet size and transmission rate on maximum delay.

It can be seen from the broken line diagram that when the transmission rate is designed to be 0.01s and 0.03s, the corresponding data packet will lose. The corresponding data

TABLE 5. Effect of different data sizes and transmission rates on internal delay.

Packet (B)	Delivery rule (s)						
	0.03	**0.04**	**0.05**	**0.06**	**0.07**	**0.08**	**0.09**
1300	41.23	42.19	41.10	42.89	42.10	41.65	42.00
1200	42.19	41.11	41.32	41.89	41.12	41.32	43.24
1100	61.89	62.31	64.33	61.01	62.11	64.00	63.42
1000	55.23	54.12	54.11	53.50	53.12	51.67	54.12
900	47.12	49.56	49.50	48.16	48.90	49.56	48.92
800	62.12	63.19	63.00	63.39	62.98	62.99	63.09
700	59.33	60.54	60.52	60.59	61.02	60.19	60.99
600	58.12	59.15	59.12	59.32	58.43	59.10	59.32

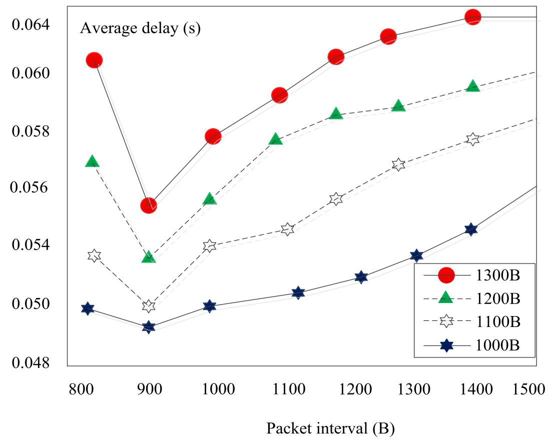

FIGURE 15. Overall delay of moving medical data from data source node to data center storage in cloud-end hardware-in-the-loop simulation model.

packet size is designed to be 1300B, and the corresponding transmission effect is the best when the transmission rate is designed to be 0.02s, and the corresponding transmission delay is the smallest.

In order to further verify the advantages of the improved convolutional neural network algorithm proposed in this paper. Based on the cloud-based hardware-in-the-loop simulation platform proposed in this paper, several common models are compared with the improved deep learning algorithms model. The main technical indicators are the test accuracy when the input is time series data and the test accuracy when the data is correlation coefficient. There are three main models compared with the improved deep learning algorithm: convolution neural network model, neural network model and machine learning algorithm. In this experiment, 20 classified experiments were carried out, and the data in each experiment were cross-validated, the corresponding experiment guarantees the same size of data packet, and the corresponding data packet size and transmission rate are guaranteed to remain unchanged (the transmission rate of the corresponding 20 experiments is 0.02s, and the corresponding data packet size guarantees the same amount of data in each

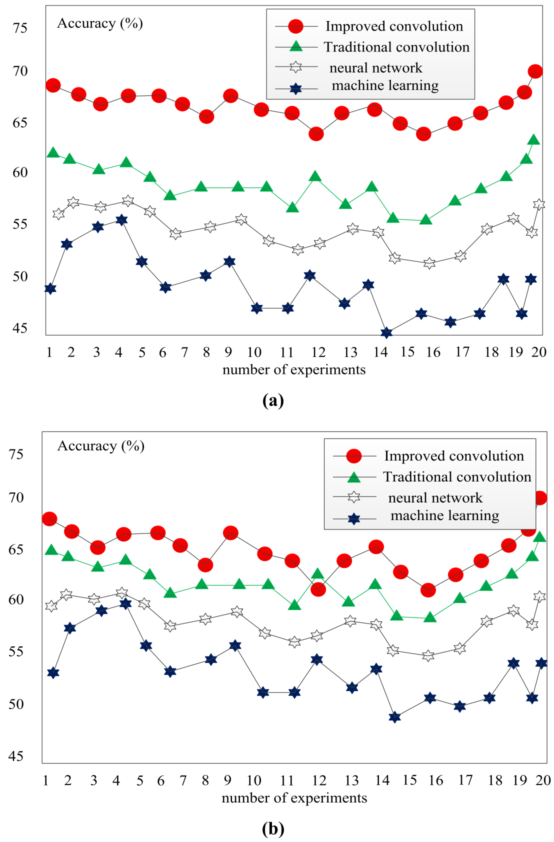

FIGURE 16. **(a) Test accuracy of time series data input. (b) Test accuracy of data input as correlation coefficient.**

experiment). At last, the corresponding average and standard deviation were obtained, so as to compare different model performances. The corresponding model test accuracy broken line diagrams are shown in Figure 16 (a) and Figure 16 (b). As can be seen from Figure 16 (a) and Figure 16 (b), the data classification accuracy of the improved convolutional neural network model is about 70%. The corresponding convolutional neural network model, neural network model and machine learning algorithm get 61%, 55% and 56% data classification accuracy respectively.

In addition to accuracy testing, this paper also verifies the diagnostic accuracy of improved convolutional neural network model, traditional neural network model, neural network model and machine learning algorithm model based on cloud-based hardware-in-the-loop simulation system. The corresponding experimental network layer is guaranteed to be four network layers corresponding to each other: input layer, convolution layer, pooling layer and output layer. As shown in Figure 17, the diagnostic accuracy of Improved Convolutional Neural Network and Traditional Neural Network methods above can reach 98% theoretically with the same number of basic layers. Compared with other models, the improved neural network model proposed in this paper has obvious advantages.

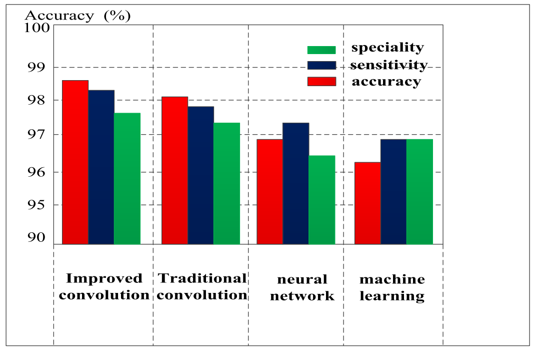

FIGURE 17. **Comparing and analyzing diagrams of diagnostic accuracy of four models.**

V. CONCLUSION

With the increase of sports medical data year by year, the requirement of data processing and analysis technology is becoming higher and higher. With the huge increase of data, traditional deep learning algorithm appears weak and inefficient in sports medical data mining. Therefore, efficient and precise sports medical data mining methods are very important and meaningful. In order to solve the above problems, this paper systematically analyses and studies the disadvantages of the current convolution neural network algorithm combined with sports medical data, and improves the convolution neural network algorithm based on the resampling algorithm with self-adjusting function. In order to process huge amounts of data more accurately, this paper also innovatively introduces the auxiliary model tensor convolution self-coding neural network model to realize the analysis and processing of multi-dimensional data of sports medicine. Finally, in order to further realize the construction of intelligent medical data platform for sports medicine, this paper designs and builds a cloud-based fusion hardware-in-the-loop simulation model, and carries out systematic analysis and Research on the model, thus providing technical support and experience for the real cloud-based fusion hardware-in-the-loop system. Overall, the work of this paper is relatively complete, but due to the limited space, the follow-up work will focus on the application and analysis of improved convolutional neural network in time series data feature learning, in order to achieve efficient processing and analysis of sport medical image data.

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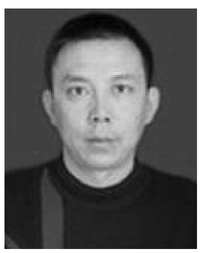

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