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Research Article

Application and Implementation of Deep Learning for Evaluation of Martial Arts Trainings

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The Chinese name for martial arts is known as Wushu; it is a typical Chinese sport in which both internal and exterior actions are emphasized. Wushu training evaluation is a hot research area, and deep learning has long been an essential tool for ensuring and promoting continuous development in the quality of Wushu training assessment. The deep learning-based martial arts training programme successfully processes and analyses the massive raw data produced throughout the teaching process at colleges and institutions. The online learning behavior is obtained by training the detection model of target, model for detection of face, and face segmentation model and then merging them with the online system. Feature extraction, offline performance prediction, learning law analysis, and personalized learning recommendation can provide decision support for training of martial arts evaluation as well as the formulation of related improvement measures. It can successfully increase the teaching quality of teachers and the learning efficiency of students by catering to the current online and offline combination of new learning and teaching techniques. In this paper, a martial arts training evaluation model based on deep learning technology is presented in light of the variety and vast quantity of martial arts training evaluations, using MatConvNet to build a deep neural network and organically fuse various raw data of martial arts training evaluation. The proposed approach provides a more accurate assessment of martial arts training and has some practical applications. In experimental evaluation of the model, it is obtained that the network's prediction performance is at its greatest value when the combination number of layers are eight.

1. Introduction

The formal name is Wushu for Chinese martial arts; however, it can also refer to any martial art category. Wushu is a classical Chinese sport in which both internal and exterior actions are considered. In an attempt to nationalise the practice of traditional Chinese martial arts, Wushu was founded in the People's Republic of China after 1949. Government-appointed bodies created the majority of current competition forms (Taolu) from its parent arts. Wushu has now become an international sport due to the International Wushu Federation (IWUF), which hosts the World Wushu Championships every two years in Beijing; Yuan Wen Qing won the first World Championships in 1991. Wushu is also known as Kung Fu [1].

Wushu training evaluation might be described as the extent to which a school's abilities are promoted and conform to the school's educational goals, integrity, and ability goals for school-run businesses [2]. With the reform of the Wushu training evaluation system, the focus of the teaching project has shifted such that how to efficiently process and analyse the large original data acquired in the teaching process of colleges and universities, as well as how to enhance the Wushu training assessment [3]. Among the most critical protection and to promote the quality improvement indefinitely of Wushu training evaluation, it is getting researched extensively, which can provide decision support for Wushu training evaluation and the formulation of related improvement measures [4]. However, due to the development of Internet and smart phones, various disadvantages arise in the training classrooms of Wushu in colleges and universities. Students, who missed classes, refuse to practise, and spend their time on phones or playing online games, all of which have a negative impact on the

evaluation of Wushu teaching and training. Because of the advancement of the Internet, online learning has become increasingly significant in the education of today's students [5]. Today's classrooms are not only limited to school classrooms, but the students can also learn their lessons independently through the Internet outside the class. Most precisely, it relates to the extent with which students' knowledge mastery, ability growth, and quality improvement satisfy the course objectives, once a course's instruction is completed [6]. However, online learning should not be aimless, and its content must be relevant to students' interests, study habits, and school curriculum that make the learning process more systematic and efficient as well as an assessment for the degree of change in knowledge and its abilities [7].

At present, domestic and foreign colleges as well as universities have carried out multilevel research on the evaluation of Wushu training [8]. The evaluation index mechanism is primarily applied to assess educational activities, student learning effects, and feedback, after which the representative system is calculated by weighing the index method or using mathematical models. The "intelligent teaching system" refers to adding technologies such as face recognition, microexpression analysis, and gesture recognition, online learning behavior analysis to traditional classroom teaching, to obtain intelligently students' attendance rates and learning efficiency [9]. To build an intelligent teaching environment, researchers designed the index system for different teaching processes [10]. The designed index is a term that expresses the standardization degree of teaching program execution as well as teaching efficiency utilization resources such as teachers rate the quality of their teaching activities by evaluating their actions; an intelligent teaching system that combines online and offline learning makes learning more efficient [11]. Teachers and students can make full use of existing teaching resources, save manpower as well as material resources, and maximize learning efficiency [12].

There are now two major challenges in assessing and evaluating martial arts instruction at colleges and universities. Initially, the variety and quantity of original instructional data are enormous, making conventional assessment approaches dependent on formulae to compute indicators difficult to provide efficient evaluation [13]. The learning performance prediction process built on the backpropagation (BP) neural network, the online learning behavior law analysis method based on actual entropy, and the emotion classification method analyzing online learning behavior based on microexpression are to mine the relationship between user learning emotion and efficiency, as well as to realize individuality [14]. Second, teaching involves a highly subjective activity that is governed by extremely complicated internal laws [15]. In the broadest sense, employing an analytical model to achieve a more accurate assessment of the actual situation is tough [16]. Because of this, the current evaluation of martial arts training in colleges and universities is based on teaching supervision and objective indicators (for example, the score of tests, attendance, homework, etc.).

In recent years, deep learning has become a particularly active field of machine learning research. By expanding the model's depth and breadth, that is, by increasing the number of processes and channels from the model's input to output, as well as increasing the parameter scale of the model, this is capable of expressing complex functions [17]. Since Professor Hinton's article on deep neural network training methods was published in "Science" in 2006, deep learning has quickly become a research hotspot and has been widely used in image classification, face recognition, speech recognition, artificial intelligence, etc. [18]. The application of deep learning in the evaluation of martial arts instruction is suitable. A wide proportion of successful application scenarios demonstrate that deep learning models are particularly good in managing with data variety and extracting complicated hidden rules, as well as evaluating the modelling ability and experience of experts [19]. To address the abovementioned obstacles and challenges, a deep learning model-based martial arts training evaluation model is proposed. This study provides an in-depth learning-based Wushu training evaluation method. Due to the epidemic's causes, such as online personality evaluation and offline classroom quality two-way evaluation, the establishment of video Wushu training teaching supervision, online Wushu body evaluation, online random supervision and evaluation, as well as the implementation of the above steps are evaluated using supervision experience [20]. On the classroom side, teacher side, educational administration side, student side, and cloud server, our offline module creates a two-way assessment mechanism for the quality of Wushu training classrooms. In the areas of training field, classroom attendance, training field behavior, and training expression analysis, it employs the target detection model, face detection model, and body model, as well as its feedback analysis.

The remainder of this work is structured as follows: In Section 2, martial arts training evaluation approach based on deep learning is presented. In Section 3, direction vectors are discussed. Finally, this paper is concluded in Section 4.

2. Martial Arts Training Evaluation Approach Based on Deep Learning

The proposed model is a deep neural network with normalized input layers, fully connected layers, and shielded layers. The input layer is a set of neurons with real-valued inputs. After normalizing the input, the result is sent to the fully connected layer next to it. The normalization function of the input layer, as shown in the following equation:

$$v = \frac{v - v_{\min}}{v_{\max} - v_{\min}}, \tag{1}$$

where V is the input data component and $V_{\min}$ and $V_{\max}$ represent the maximum and minimum values of this component in the training dataset, respectively. After the input layer is normalized, the resulting values are in the interval of [0, 1].

Each neuron in a fully connected layer has edges connected to all neurons in its adjacent layers, and each edge has a weight in the range of [0, 1]. All the inputs are first

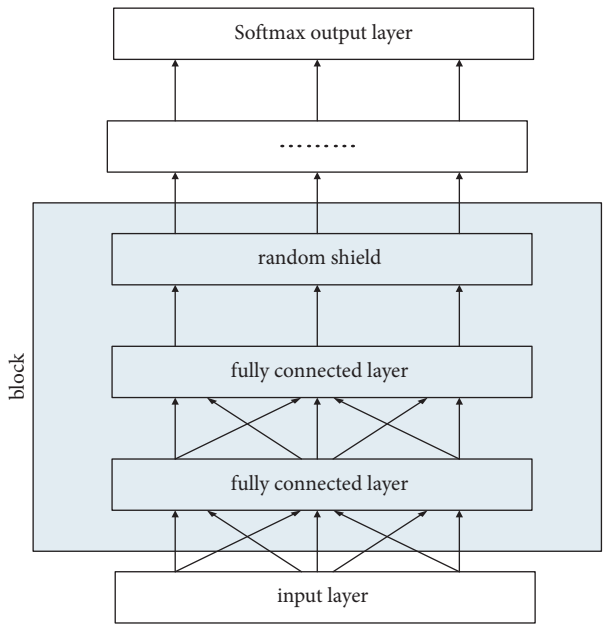

Figure 1: Schematic diagram of deep neural network structure.

weighted, summed, and then fed into a nonlinear activation function. This paper uses the sigmoid function to obtain a real-valued output, as shown in the following equation:

$$f_i = \frac{1}{1 + \exp\left(\sum_{j=1}^{M} w_{ji} v_j\right)}, \tag{2}$$

where f_i is the output of the i-th neuron in the fully connected layer, M is the number of neurons in the previous layer, V_j is the input of the j-th neuron in the previous layer, and W_{ji} is the j-th neuron connected to the previous layer of neurons. The weight of the edge between the neuron and the current neuron can be calculated by equation (2).

The shielding layer makes the output of the neurons in the previous layer to zero according to a preset percentage, while the neurons whose output is not zero in this layer are fully connected to all the neurons in the next layer. In this work, the preset random mask percentage is 30%. A masking layer exists between every two fully connected layers behind the complete deep neural network, and the number of such combinations required depends on the problem's complexity. The fundamental construction of a deep neural network is shown in Figure 1.

Finally, the evaluation score of the model is obtained using the softmax output layer for martial arts training evaluation. The softmax function performs successive maximization evaluations on the input components. Let $V = (V_1, V_2, \ldots, V_n)$, the softmax function calculates the standard value of the largest component in V in a continuous manner, namely, as shown in the following equation:

$$S_i = \frac{e^{v_i}}{\sum_j e^{v_i}}. \tag{3}$$

The training of the network adopts the method of error back-propagation gradient descent. Based on the directional derivative of the multivariate function, the error of each neuron is calculated from the back to the front, after that the weight of the connection between the neurons is adjusted accordingly. The specific calculation method is shown in the following equations:

$$\frac{\partial f(x + \alpha u)}{\partial \alpha} = u^T \nabla f(x), \tag{4}$$

$$u^* = \min_{u, u^T, u=1} u^T \nabla_x f(x) = \min_{u, u^T, u=1} \|u\|_2 \left\|\nabla_x f(x)\right\|_2. \tag{5}$$

In the above equations, u is the direction vector modulo one, u^* is the optimal direction vector, $\nabla_x f(x)$ is the error value of the neuron, and $\|\cdot\|_2$ is the second norm. By adjusting the training intensity, the convergence speed of the network during the training process can be changed.

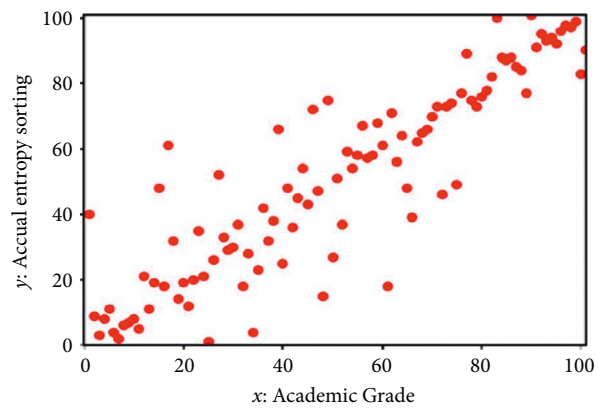

Figure 2: Scatterplot of Spearman correlation for actual entropy.

3. Direction Vectors

All training techniques must be implemented in accordance with the movement form. Martial arts training evaluation is a skill with high technical requirements, and the procedural training method is mostly represented in the following areas in the training of martial arts techniques and motions. The Wushu training program's training elements are essentially the Wushu training content that must be completed. The training items provided by the training program are essentially the logical and qualitative reflection of the internal relationship for each training content and its subfactors, while the series of indicators provided by the evaluation standard are essentially the identification marks to judge the difference between the actual state and the training program. As a result, deep learning may be based on the current state of martial arts trainers, modify training goals, correct the skewness of the training process, and place the future martial arts training evaluation process in a feedback control condition, as indicated in the following equation:

$$G = g \times 70\% + e \times 30\%. \tag{6}$$

Table 1: Main indicators of teaching data (parts).

	Expert and student evaluation data		
1	Student attitude	Continuous	0–100
2	Teaching	Discrete	Fifth gear
3	Teaching plan	Discrete	Fifth gear
4	Student atmosphere	Discrete	Fourth gear
5	Student evaluation	Questionnaire	Multiple questions
	Objective indicator		
1	Usual grades	Continuous	0–100
2	Overall rating	Continuous	0–100
3	Attendance	Continuous	0–100%
4	Transfer rate	Continuous	0–50%

Table 2: Structure of the deep neural network.

No.	Type	Input	Output	Function
1	A	60	60	N/A
2	B	60	120	Relu
3	B	120	240	Relu
4	C	240	240	30%
5	B	240	480	Relu
6	B	480	960	Relu
7	C	480	480	30%
8	B	480	960	Relu
9	B	960	960	Relu
10	C	960	960	50%
11	D	960	8	Softmax

The Spearman correlation coefficient is used to determine the link between the two variables. The formula indicated as follows:

$$rs = \rho_{rgx,rgy} = \frac{\mathrm{cov}\left(rg_x, rg_y\right)}{\sigma_{rgx}\sigma_{rgy}}. \tag{7}$$

Among them, rg_x represents the real grade ranking, r_{gy} represents the time difference ranking, cov(rg_x, rg_y) represents the covariance of the rank variable, and rg_x, rg_y represent the standard deviation of the rank variable.

Using the original teaching data collected during the undergraduate teaching process of our school, as shown in Figure 2, it is mainly divided into two categories, in which the first one is the evaluation index of experts and students, while the second one is the objective index. Table 1 depicts the specific circumstance (parts) of the two indicator groups.

The student evaluation indicators in Table 1 are a questionnaire with 20 multiple-choice questions. In this study, we converted the answer to each multiple-choice question into a Boolean vector and fed it into the model.

The scale of the entire dataset is 67,188 pieces of teaching evaluation information for 106 professional courses in five academic years. Each piece of teaching evaluation information contains 26 fields, some of which are shown in Table 1. Input continuous fields straight into the model, and the normalization input layer will normalize the data. For discrete fields, Boolean vectors are encoded 1-of-k and then supplied into model training. Each piece of teaching evaluation data is enlarged to 64 dimensions after processing. A 6-dimensional goal vector is included with each piece of teaching evaluation information to indicate the martial arts training evaluation expressed by the teaching evaluation information.

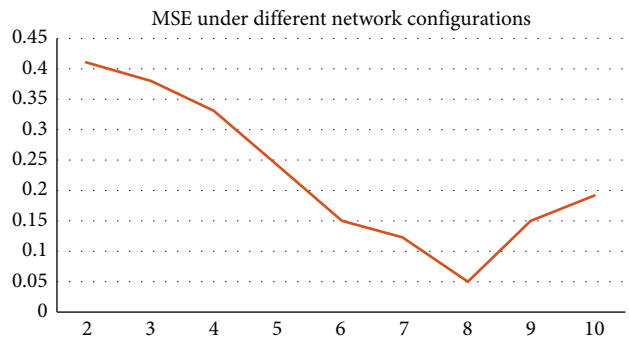

Figure 3: The effect of combining fully connected and shielding layer prediction results.

The evaluation model is a deep neural network, and the model structure is given in Figure 1. The deep neural network depicted in Table 2 is employed in this application.

The A, B, C, and D letters are used in the column named as "Type" to represent the normalized input layer, fully connected layer, shield layer, and output layer, respectively. The input and output columns represent the dimensions of the input and output for each layer. The Function column represents the activation function for each layer, and the proportion of random masking for class C masking layers is shown by the column.

The implementation and training of the entire model are carried out in the famous deep learning project MatConvNet, which is based on Matlab's deep learning algorithm implementation, including network configuration, training algorithms, and various mainstream trained network models.

In order to verify the effectiveness of the model, the dataset is divided into two parts, the training set and the test set, with a ratio from 1 : 9 to 9 : 1. First, use the training set to train a deep neural network, and then use the data from the test set to train a deep neural network. Provide input to the trained neural network, get a series of outputs, compare the output to the real output of the test set, and calculate the error. Given that the output is a 6-dimensional real-valued vector indicating the evaluation of martial arts instruction, we use the mean squared error to measure the difference between the output and true values, as shown in

$$\mathrm{loss} = \frac{1}{N}\sum_{i=1}^{6}\sum_{j=1}^{N}\left(h_{ij} - h_{ij}^{*}\right), \tag{8}$$

where h_{ij} is the i-th output component of the model for the j-th test sample. The test results are displayed in Figure 3 for each scale of the dataset that is randomly divided 10 times.

The mean square error (MSE) is calculated by using equation (8) to determine the test error of the model. As can be seen from Table 2, when the ratio of the training set to the test set is 6 : 4, the test error of the model is the lowest. At the same time, it should be emphasized that the model's effect does not improve with more training data. This is because if

there is too much training data, the model will overfit the current data, causing the model's generalization capacity to be reversed or reduced.

Simultaneously, as shown in Figure 3, we report on the impact of various deep neural network configurations on model prediction results. The number of BBC-type layer combinations in the network has been increased from 2 to 10. For each configuration, we need to run the training and prediction of the network once and record the MSE, and the results are shown in Figure 3. It can be seen from the figure that when the number of combinations is 8, the prediction performance of the network reaches the best value.

4. Conclusions

Martial arts is a most popular sport in China for which the second name is Yushu. With the development of Internet and other technologies, various issues arise in the training classrooms of Wushu in colleges and universities. Students missed their classes, refuse to practice, and spend their time on phones or playing online games, all of which have a negative impact on the evaluation of Wushu teaching and training. Therefore, the ultimate purpose of this research is to develop a set of application in martial arts training evaluation based on deep learning. The proposed system can identify the martial arts training movements of students, conduct grade evaluation, as well as give the correctness of the martial arts movements in the future. If a wrong action is taken, judgement can point out the flaw in the activity and recommend solutions to correct it. In addition, the system will give a variety of teaching videos as well as competitive recordings from world-class events to assist students in evaluating martial arts training without the assistance of a coach. It is believed that this sports training system will bring fun and health to more people, as well as provide broad application prospects. The application in the evaluation of martial arts training in this study can be scored, which can help users improve their technical level. We will further organize the original data of martial arts training evaluation and introduce new deep learning models with stronger expressive ability and more effective evaluation system to establish a more intelligent evaluation model.

Data Availability

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

Conflicts of Interest

The author declares that he has no conflicts of interest.

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