Hindawi
International Transactions on Electrical Energy Systems
Volume 2023, Article ID 9759386, 1 page
https://doi.org/10.1155/2023/9759386

Retraction

Retracted: Emei Martial Arts Promotion Model and Properties Based on Neural Network Technology

International Transactions on Electrical Energy Systems

Received 15 August 2023; Accepted 15 August 2023; Published 16 August 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets 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 own 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] C. Xing, N. Z. Abidin, and Y. Tang, "Emei Martial Arts Promotion Model and Properties Based on Neural Network Technology," *International Transactions on Electrical Energy Systems*, vol. 2022, Article ID 6906844, 10 pages, 2022.

Hindawi
International Transactions on Electrical Energy Systems
Volume 2022, Article ID 6906844, 10 pages
https://doi.org/10.1155/2022/6906844

Research Article

Emei Martial Arts Promotion Model and Properties Based on Neural Network Technology

Cheng Xing ,[1,2] N.E. Zainal Abidin,[1] and Yudong Tang[2]

[1]*Center for Sport and Exercise Sciences, University of Malaya, Kuala Lumpur 50603, Malaysia*
[2]*Institute of Physical Education, Neijiang Normal University, Neijiang 641000, Sichuan, China*

Correspondence should be addressed to Cheng Xing; 10001321@njtc.edu.cn

Received 27 July 2022; Revised 24 August 2022; Accepted 2 September 2022; Published 24 September 2022

Academic Editor: Raghavan Dhanasekaran

China unanimously believed that Emei Martial Arts has the essence of self-improvement. It is a spiritual force that actively promotes human progress. It should be protected and continuously innovated to make it a spiritual pillar of people. However, its promotion faces huge challenges. In recent years, neural networks have made great progress in various fields, such as speech recognition, computer vision, and natural language understanding. On this basis, the combination of neural networks and traditional recommendation methods is helpful for the better development of Emei Martial Arts promotion. Neural networks have a direct analog interaction function and perform coordinated filtering directly through interactive data. Due to the effectiveness of the structure, the neural network can mine nonlinear implicit relationships from the data and find the martial arts items that users want to promote. In order to enhance the effectiveness of the standard recommendation algorithm, a deep neural network-based recommendation algorithm is paired with a neural network-based recommendation algorithm that is proposed in this article. The recall rate of the upgraded deep neural network recommendation model is up to 80%, whereas the recall rate of the model without enhancement is up to 40%, according to the experimental results of this article. The upgraded deep neural network's recommendation model has a recall rate that is 4% greater than the baseline model. It showed that the recommendation algorithm combined with a neural network has a better recommendation effect so as to achieve a better effect of Emei Martial Arts promotion so that Emei Martial Arts culture can be carried forward and economic development can be promoted at the same time.

1. Introduction

Emei Martial Arts refers to the martial arts inherited by monks in Buddhist monasteries with Mount Emei as the main body, developed in Mount Emei, or spread from Mount Emei to other areas during the 1700-year process of the origin, formation, and development of Buddhist culture in Mount Emei. Emei Martial Arts itself is a cultural symbol, and it is of great significance in cultural history. It is an important force for the continuation of traditional national culture and Chinese martial arts culture. The development of Emei Martial Arts to this day is a special form and special significance of Wushu, which is the intangible cultural heritage of the country, an important representative of the technical content of martial arts, and an important symbol of the national cultural heritage background. Therefore, how to enhance the promotion of martial arts culture in the Internet age has become an important topic.

Although Emei Martial Arts originated in China, it is popular all over the world and is the precious wealth of all human beings. In the context of globalization, Chinese traditional martial arts need to go to the world. This is the call of the times and the needs of the country. Spreading the traditional martial arts of excellent Chinese culture to all parts of the world so that people all over the world can feel the breadth and depth of Chinese culture and the great wisdom of the Chinese people so as to create a good image of the Chinese people and improve China's international status, to increase China's worldwide influence and, ultimately, to raise China's standard of living. The innovation of this paper is to propose an Emei Martial Arts promotion model based on the combination of neural networks and recommendation algorithms. The model combining neural network and recommendation algorithm is not only higher than the traditional recommendation algorithm in terms of recommendation accuracy but also better in terms of recommendation effect.

2. Related Work

As China's international status is getting higher and higher, people are paying more and more attention to Chinese traditional culture. As an important part of traditional Chinese martial arts, the promotion of Emei Martial Arts has also attracted people's attention. Moore et al. found that mental health problems in martial arts learning are increasingly concerned by the public, but they are often not treated well for various reasons. He investigated the potential value of martial arts instruction as an exercise-based mental health intervention. Martial arts are viewed as a therapeutic process or as a psychologically transformative practice [1]. The purpose of the Kwak and Yoo study was to examine the martial arts promotion model and to provide basic data that can increase interest in martial arts in the future by indirectly experiencing the essence of martial arts. In modern society, martial arts is approaching the public in various forms. It has become the essence of "practice" and "strengthening the body" in a new culture [2]. Zhang et al. found that Tai Chi is an important component of Emei Martial Arts, and now many college students are practicing Tai Chi. He conducted experiments on whether Tai Chi can develop the cognitive function and what the effective frequency is [3]. He et al. studied the robust state estimation problem of a class of uncertain neural networks with time-varying delays, and the results showed that the robust state of such neural networks could be easily achieved by using some standard numerical packages [4]. Yang et al. proposed a simple yet effective supervised method for large-scale image search. It can be achieved with slight enhancements to existing deep classification architectures and outperforms other hashing methods on multiple benchmarks and large datasets [5]. Scholars believe that Emei Martial Arts should be popularized, but there are many problems with the current promotion methods. In order to solve these problems, it is necessary to study the promotion model of Emei Martial Arts with the help of modern science and technology. However, scholars have not proposed detailed research methods.

Neural networks have gained significant ground in artificial intelligence and big data during the past few years, making significant strides in speech recognition, natural language processing, computer vision, and other areas. The use of neural networks in extension systems is the subject of expanding research. Mei et al. discovered that one of the most effective machine learning models is the multilayer neural network. The optimization of a nonconvex high-dimensional objective required for learning a neural network is typically accomplished via stochastic gradient descent [6]. Wang et al. investigated the global stability issue of piecewise constant parameter fractional-order neural networks. He began by putting forth an inequality regarding upper bound integral derivatives, which not only helps with function creation but also expands upon the theory of fractional calculus. The last example is provided to show the applicability of the findings [7]. For the purpose of training deep neural networks with quantized weights, Yin et al. suggested a straightforward two-stage technique. Representation weight quantization ensemble limitations are not enforced until late in the training process [8]. Cheng et al. found that deep neural networks have received increasing attention in recent years. It has been applied to different applications and achieved significant accuracy improvements in many tasks. The availability of graphics processing units with very high computing power plays a key role in their success [9]. Scholars found that neural networks can be combined with recommendation algorithms to achieve the purpose of establishing the Emei Martial Arts promotion model. The neural network has the ability of self-learning and self-adaptation, which can effectively find the martial arts items that users are interested in. It can grasp the aesthetics of the public to promote martial arts. However, scholars have not elaborated on how to combine neural networks with recommendation algorithms.

3. Martial Arts Recommendation Algorithm Based on Deep Neural Network

Emei Martial Arts is an important part of Chinese traditional culture, and it is a traditional national sports activity used by the Chinese people for thousands of years to keep fit, defend the country and entertain [10]. Due to its historical development, geographical distribution, and different practice groups, Chinese martial arts have derived from different schools and different styles of regional martial arts content and forms, such as Shaolin martial arts based on the regional culture of the Central Plains, Wudang martial arts based on the regional culture of Jingchu, and Emei martial arts based on the regional culture of Bashu. Whether in the past, present, or future, have a positive and far-reaching impact on popular culture, group consciousness, moral concepts, and social life in Chinese society. The significance of Emei Martial Arts promotion is shown in Figure 1.

As shown in Figure 1, traditional martial arts has never withdrawn from the stage of historical development. The development and progress of the times and the change in people's ideology have put forward higher development demands for traditional martial arts. It is the demand of the times to continuously innovate traditional martial arts. Continuous promotion and popularization, participation in national fitness programs, and continuous improvement of self-integration into international cultural exchanges are the correct way for the sustainable development of martial arts.

The problems of traditional martial arts in the promotion mode include the following: lack of economic support, lack of policy support, lack of creativity, and lack of a sound organizational system, which makes martial arts encounter a bottleneck in the promotion.

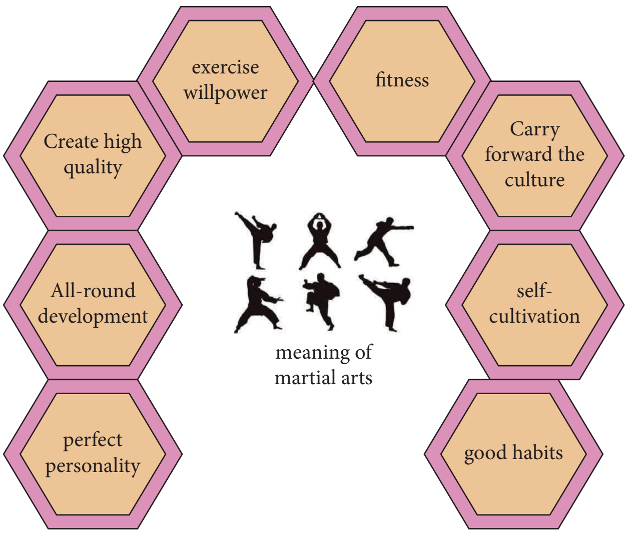


Figure 1: Significance of emei martial arts promotion.

3.1. Hybrid Recommendation Algorithm. A recommendation algorithm is an algorithm in the computer profession. Through some mathematical algorithms, it can be inferred what users may like. At present, the best place to apply recommendation algorithms is mainly the Internet. The pros and cons of recommendation systems are usually evaluated using evaluation indicators. The methods of evaluating the system mainly include online evaluation, user survey, and offline evaluation. Various experimental methods have advantages and disadvantages [11]. Among them, offline evaluation is the most commonly used experimental method. Its experimental conditions are simple, and the cost is low, so it is very popular among researchers. There are many evaluation indicators for the three experimental methods, which can be mainly divided into accuracy indicators, classification accuracy indicators, and error indicators. A brief introduction to each of the three categories is as follows.

Mean absolute error is the average of the absolute values of the deviations of all individual observations from the arithmetic mean. The mean absolute error can avoid the problem of mutual cancellation of errors, so it can accurately reflect the size of the actual prediction error. In the recommendation system, the difference between the system recommendation score and the user's actual score is an important indicator to measure the accuracy of the recommendation system. One of the most commonly used methods is the mean absolute error [12]. Its calculation formula is formula (1) as follows:

$$\mathrm{MAE} = \frac{\sum_{u,i\in T}\left|r_{ui} - \hat{r}_{ui}\right|}{T}. \tag{1}$$

In addition to MAE, there are mean square error, root mean square error, and standard mean square absolute error, which are often used for evaluation. Their calculation formulas are as follows:

$$\mathrm{NMAE} = \frac{\mathrm{MAE}}{r_{\max} - r_{\min}},$$
$$\mathrm{MSE} = \frac{\sum_{u,i\in T}\left(r_{ui} - \hat{r}_{ui}\right)^2}{|T|}. \tag{2}$$

$r_{\max}$ and $r_{\min}$ represent the upper and lower limit values within the user rating data, respectively. The formula for calculating RMSE is as follows:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{u,i\in T}\left(r_{ui} - \hat{r}_{ui}\right)^2}{|T|}}. \tag{3}$$

Among them, T represents the test dataset,r_{ui} represents the actual rating of item i by user u. $\hat{r}_{ui}$ represents the predicted rating for item i [13]. The average accuracy formula is shown as follows:

$$\mathrm{MAP} = \frac{1}{U}\sum_{u\in U}\frac{\sum_{u\in U}|R(u)\mathrm{I}T(u)|}{N}. \tag{4}$$

N represents the number of recommendation lists, and the classification accuracy index is usually used to evaluate whether the recommended items provided by the recommendation system to users are popular with users [14]. The formula for calculating the recall rate of the classical classification precision index is shown as follows:

$$\mathrm{reacall} = \frac{\sum_{u\in U}|R(u)\mathrm{I}T(u)|}{\sum_{u\in U}|T(u)|}, \tag{5}$$

$T(u)$ represents all the items that the user likes on the test set.

3.2. Recommendation Model Based on Deep Neural Network. The deep neural network is a technology in the field of machine learning. In supervised learning, the problem of previous multilayer neural networks is that it is easy to fall into local extreme points. If the training samples are enough to fully cover the future samples, then the learned multilayer weights can be well used to predict new test samples. Artificial Neural Network (ANN), also known as Neural Network, is a technology that simulates intelligent human behavior. To simulate the ability of the human brain, a single neuron is not enough, and multiple neurons are needed for information transmission and cooperation [15]. Multiple neurons are connected in a specific way to form a neural network. Both single-layer and multilayer perceptrons are frequently used in neural networks. A hidden layer is inserted between the input layer and the input layer to create the output layer of a multilayer perceptron, while a single-layer perceptron typically solves linear classification problems. Figure 2 depicts the multilayer neural network.

As shown in Figure 2, multilayer perceptron (MLP) is a simple and efficient model that can learn nonlinear functions. It is widely used in many fields, especially in the industrial field. Since the learning algorithm used is the BP

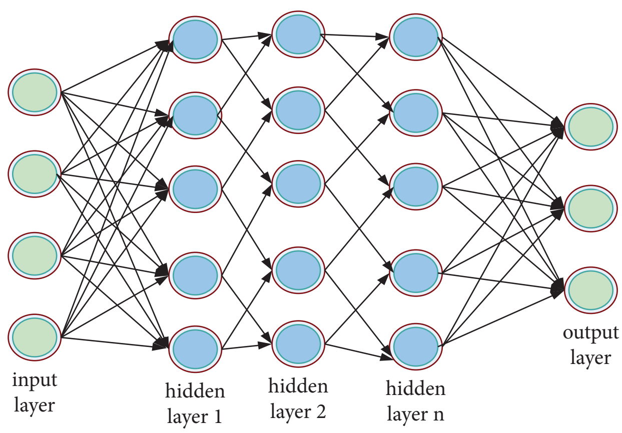


FIGURE 2: Multilayer neural network.

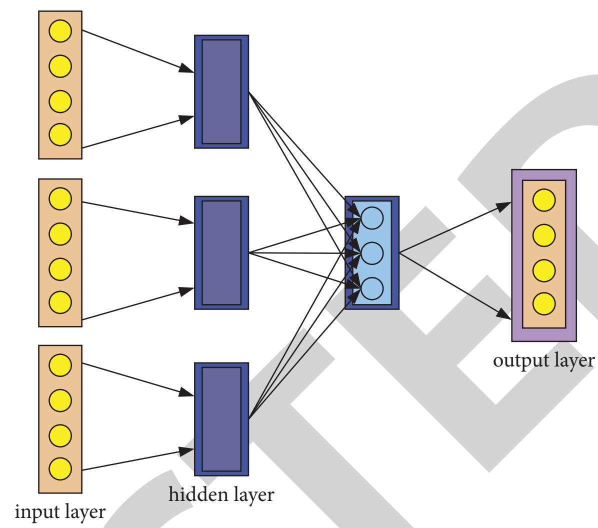


FIGURE 3: Skip-gram model.

algorithm, MLP is also called BP neural network. MLP represents approximate measurable functions with arbitrary precision and is the basis of many advanced models [16, 17].

The modified linear unit is an activation function often used in deep neural networks, and its function image is specifically defined as follows:

$$\mathrm{relu}(a) = \begin{cases} a, a \geq 0, \\ 0, a < 0. \end{cases} \tag{6}$$

The RELU function is actually a piecewise linear function, which changes all negative values to 0 while the positive values remain unchanged. This operation is called unilateral inhibition. With unilateral inhibition, the neurons in neural networks also have sparse activation. The neural network using the relu function is mainly based on addition, multiplication, and comparison operations, which can be calculated efficiently. In addition, biological neurons only selectively respond to a few input signals, and the neurons in the active state are very sparse, so relu can effectively reduce the problem. The neural network is mainly trained with self-learning in the case of a vanishing slope [18]. The Skip-gram model is shown in Figure 3.

As shown in Figure 3, soft max reduces the computational complexity of target probability by constructing a binary tree but enhances the coupling between words [19]. In practical applications, the original likelihood function of the kip-gram model corresponds to a multinomial distribution. When using the most-likelihood method to solve the likelihood function, a loss function or cost function is a function that maps a random event or the value of its related random variable to a nonnegative real number to represent the "risk" or "loss" of that random event. The loss function is shown as follows:

$$J(\theta) = -\frac{1}{T}\sum_{t=1}^{T}\sum_{-c \leq j \leq c, j \neq 0} \log p\left(w_{t+j}|w_t\right). \tag{7}$$

Softmax function, also known as a normalized exponential function. It is a generalization of the binary classification function sigmoid in multi-classification, and the purpose is to display the results of multi-classification in the form of probability. Negative sampling modifies the algorithm to use the numerator in the original softmax function to define the logistic regression function.

This paper proposes a deep neural network recommendation model that combines user and item information. It uses user and item attribute information and item text auxiliary information to enrich the information of the original user and item data, which is beneficial to alleviate data sparsity and cold start problems and improve recommendation quality [20, 21].

To enhance the performance of recommendations, the deep neural network-based recommendation model combines user and item attribute information with item text information. The attribute features of individuals and items are obtained using a deep neural network, and the content features of the objects are obtained by processing the supplementary text data using a CNN. Next, the objects' content features and related attribute features are integrated [22].

User and item attribute information are input into a neural network to obtain user and item attribute features. Assuming that the user's attributes are a: $\{a_1, a_2 \ldots a_m\}$,a_m means that one of the user's attributes, as shown in formula (8) as follows:

$$\bar{a} = f\left(w_1 a + b_1\right). \tag{8}$$

Then the user attributes are fused to obtain the user characteristics, as follows:

$$u_i = \mathrm{concatenate}(\bar{a}). \tag{9}$$

To enable the convolution operation to be carried out in the convolution layer in accordance with the word length, the embedding layer's function is to transform the original document into a digital matrix. For instance, if a document has k words, the word vector can first be seeded with a pretrained word embedding model before each word's vector can be coupled into a matrix based on the order of the words. Therefore, formula (10) can be used to express the project document matrix D as follows:

$$D = \begin{bmatrix} w_{11} & \cdots & \cdots & \overset{1k}{w} \\ w_{21} & \cdots & \cdots & w_{2k} \\ \cdots & \cdots & \cdots & \cdots \\ w_{p1} & \cdots & \cdots & w_{pk} \end{bmatrix}. \tag{10}$$

P represents the dimension of the word embedding, and w_{pk} represents the word in the document.

The high-level features obtained from the previous layer are typically converted into specific tasks in the output layer. Projecting the latent characteristics of users and goods onto the m-dimensional space allows for the realization of the recommendation task. Finally, the latent documents are generated by using traditional nonlinear projection, as follows:

$$s = \tan h\left(w_{f2}\langle \tan h\left(w_{f1}d_f + b_{f1}\right)\rangle + b_{f2}\right). \tag{11}$$

Among them,w_{f2} is the projection matrix and w_{f1} is the bias vector. It becomes a function through the architecture of the above procedural model, which takes the original document as input and returns a latent vector for each document as output.

3.3. Improved Recommendation Model Based on Deep Neural Network. Recommendation models based on deep neural networks only use attribute information of users and items and content information of items, and do not capture other latent factors from the user's evaluation matrix of model items. Based on this, this paper adds rating information to mine more relationships between users and items to further improve the recommendation quality [23].

For high-dimensional classification problems, because there are too many nodes and too many parameters, blindly increasing the depth will only make the results more and more uncontrollable and become a complete black box. However, the use of stacked autoencoding to reduce dimensionality layer by layer can simplify complex problems and make tasks easier to complete. Stacked denoising autoencoder SDAE is an extension of denoising autoencoder DAE, which stacks multiple DAEs together to form a deep neural network structure. DAE is a neural network that adds noise to the input data on autoencoder AE [24]. Since the shallow DAE has limited ability to learn the complex features of the data, the multilayer model can better learn the feature representation of the data, so multiple DAEs can be stacked into a deeper model to form SDAE. The model is shown in Figure 4.

As shown in Figure 4, this paper combines deep learning with collaborative filtering methods to predict ratings and make recommendations for users. It described an improved deep neural network recommendation model that integrates SDAE and MLP. The upgraded deep neural network's recommendation model is a hybrid one that fully utilizes the user-item assessment matrix as well as user and item information. The user and item information are then

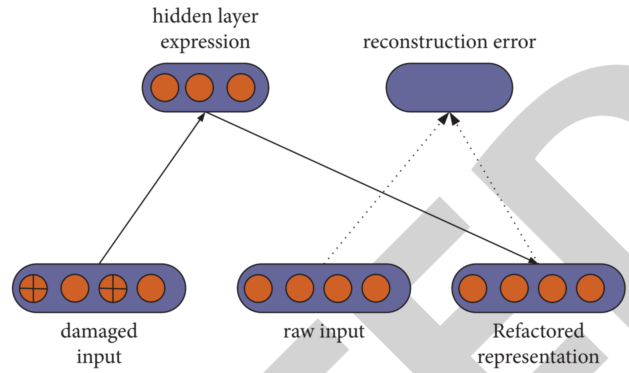


Figure 4: Sdae model diagram.

combined after using SDAE to uncover the hidden functions of users and items from the user-item evaluation matrix. Finally, users' and items' feature vectors are acquired. The multilayer classifier is then used to learn the nonlinear relationship between users and items after being fed the retrieved feature vectors of users and items.

SDAE usually uses unsupervised training. Firstly, it trains the first layer and records the training parameters of this layer. Then it trains the second layer and records the parameters of the second layer, and so on, and trains the next layer. The encoding process is as follows:

$$h = f(a) = \sigma(Wa + b1). \tag{12}$$

The calculation method for generating the features of user i is as follows:

$$u_i = \text{sdae}\left(\{A_I, P_i\}\right), \tag{13}$$

sdae represents the stack-type noise reduction autoencoder processing sparse data, and u_i represents the obtained user features. The same as obtaining the latent features of users, the latent factor for an item j consists of three parts: the attribute of the item, the rating matrix, and the item description document processed by a convolutional neural network (CNN). Therefore, the calculation method of the characteristics of user j is as follows:

$$v_j = \text{sdae}\left(\{B_i, Q_i\}\right), \tag{14}$$

v_j represents the feature of the item obtained by sdae processing the rating data and item attribute information.B_i represents the feature obtained by combining the text feature obtained by CNN processing the text information with the corresponding item feature. Q_i represents the CNN processing the text information and, W represents the weight of the CNN as follows:

$$\hat{b} = MLP\left(\{u_i, v_j'\}\right), \tag{15}$$

$\hat{b}$ represents the predicted score and MLP$(\bullet)$ represents the multilayer perceptron used to predict the score. The objective function considers the loss between all inputs and reconstruction. SDAE solves the following optimization problems:

Table 1: Survey of 100 martial arts experts.

Insufficient	Number of people	Percentage
Little government support	42	42
Little publicity	20	20
Few professionals	17	17
Fewer events	15	15
Few routes of transmission	6	6

$$\arg\min \alpha = \|P - \hat{P}\|_F^2 + (1-\lambda)(A-\hat{A})^2. \tag{16}$$

Among them,α is the balance parameter for the balanced output, and λ is the regularization parameter. The overall objective function for SDAE dealing with users and items is shown in formula (17) as follows:

$$L = \alpha_1 \sum_i \left(p_i^{(n)} - \hat{p}_i^{(n)} \right)^2 + (1-\alpha_2) \sum_i \left(a_i - \hat{a}_i \right)^2. \tag{17}$$

Among them,α_1 and α_2 represent the balance parameters of the balanced outputs of the two SDAEs, respectively.

The convolutional neural network has the ability of representation learning and can perform translation-invariant classification of input information according to its hierarchical structure. In this paper, the convolutional neural network is still used to obtain the description document features of the item because CNN can learn the sequence features of text content very well. There is a pooling operation in CNN to extract keywords in documents, and many studies now apply CNN to process text, such as natural language, using CNN, connecting the item description document features obtained by CNN with the obtained item feature v_j to obtain the total feature of the item, as follows:

$$v_j' = \mathrm{cnn}(W, B_j) v_j. \tag{18}$$

Among them,$\mathrm{cnn}(W, B_j)$ represents the feature of the item description document obtained by CNN.v_j represents the hidden feature of the item obtained by SDAE, and v_j' represents the total feature of the item for predicting the score. Finally, the recommendation prediction score is made according to the score, as follows:

$$a_0 = \mathrm{concatenate}(u, v_j'). \tag{19}$$

Algorithms provide users with martial arts items they might like and similar items to items rated by the user.

4. Experiment of Recommendation Model Based on Deep Neural Network before and after Improvement

4.1. A Survey on the Existing Promotion Mode of Traditional Martial Arts. With the improvement of China's national status, the rise of the national economy, and the deepening of the reform of the sports system, the sports and the economy intervene, penetrate, and combine with each other, and the relationship is getting closer and closer. The complementary functions of sports and the economy are bound to bring unprecedented development opportunities to sports and the market. As excellent traditional national sports, martial arts will inevitably be affected by economic growth, and the road of the martial arts industry has also begun to explore and innovate.

Through the investigation of 100 martial arts experts, it can be found that the main threats to the promotion of martial arts development are as follows: the contradictory influence between the inheritance and development of Chinese martial arts, the lack of communication channels, and insufficient propaganda. The survey results are shown in Table 1.

As shown in Table 1, the proportion of insufficient government support and insufficient publicity is the highest, up to 42% and 20%, respectively. Among them, the government does not have relevant policies, laws, and regulations to support the establishment of martial arts halls and schools for martial arts inheritors or free martial arts instructors. It has not provided enough support in organizing training and capital investment. Because traditional martial arts is a nonlocalized sport, and due to different cultures, there is insufficient support for martial arts halls and schools that focus on Chinese martial arts. The development trend of martial arts in recent years is shown in Figure 5.

As shown in Figure 5, in recent years, the development of martial arts has been getting faster and faster, and international cultural exchanges require the communicators to have relevant national cultural knowledge, local customs, folk customs and national language, and other qualities. Today, with the rapid development of competitive martial arts, traditional martial arts, which contain China's excellent national traditional sports culture and national spirit, cannot go hand in hand. Martial arts want to be simplified and competitive and to enter the Olympic Games. However, it t is reluctant to bear five thousand years of cultural traditions. The contradiction between inheritance and development restricts the development of martial arts and restricts the path of promotion. The foundation of the development of competitive martial arts is traditional martial arts. However, in the sports field dominated by competitive sports, how to solve the problem of promotion is the key to the better development of martial arts in competitive sports.

4.2. Experiments on the Recommendation Model of Deep Neural Network before Improvement. The ml-100 k, ml-1 m, ml-10 M, and amazon data sets were used for the tests, and the average value of five experiments was used as the outcome. The effectiveness of the algorithm model suggested in this work was examined in the first part of the experiment, and the performance of other algorithms was compared and

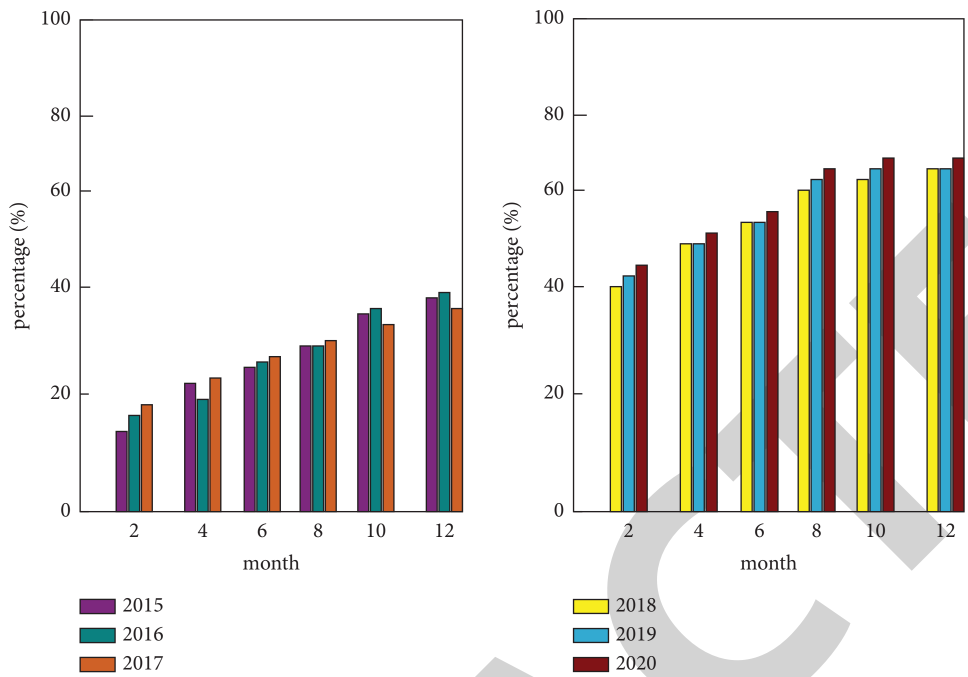


Figure 5: Development trend of martial arts from 2015 to 2020.

examined in the second. The amount of time spent training the model will have an impact on its learning outcome. The algorithm's outputs are then tested on the dataset to see how the number of iterations affects them. In Table 2, the experiment's individual root mean square error value is displayed.

According to the experimental results, as shown in Table 2, the number of iterations under the four datasets keeps growing while the RMSE of the four datasets gradually reduces, showing that the recommendation quality gets better as the number of iterations rises. Iterations between 80 and 100 are favored since the reduction of RMSE gets smaller. It can also be seen that the experimental effect of the model on the denser dataset is better than that of the sparse dataset.

The average accuracy MAP is used to describe the average accuracy of the recommendation model for each user. The larger the value of MAP, the higher the accuracy of the recommendation. The MAPs of the recommendation model before improvement and a single recommendation algorithm on different datasets are shown in Figure 6.

As shown in Figure 6, through the analysis of the results of the recommendation model before the improvement and the single recommendation algorithm on different data sets, it is evident that the recommendation model's average accuracy prior to the upgrade is higher than that of the single recommendation method. It can be seen that adding the natural attributes of the user, the natural attributes of the movie, and the description documents of the movie to the model is more comprehensive. Therefore, the higher the accuracy, the higher the recommendation quality. In addition, it demonstrates how valuable auxiliary data information is for the recommendation system and how it can help new users or products avoid the "cold start" problem.

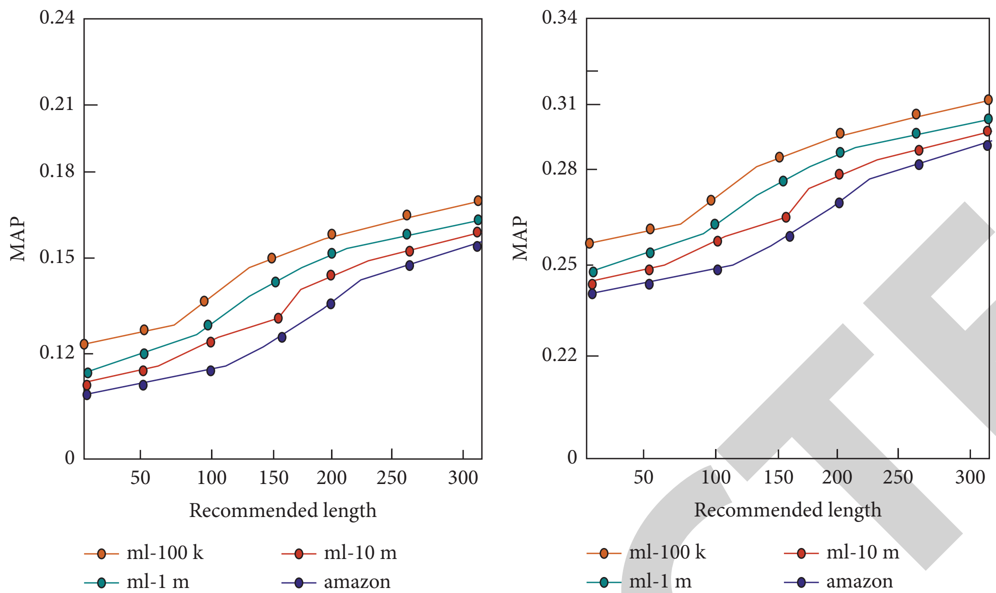
Table 2: Specific RMSE values for experiments.

Dataset	ml-100 k	ml-1 m	ml-10 m	Amazon
20	0.7921	0.6321	0.6465	0.8605
40	0.6124	0.5750	0.6909	0.8360
60	0.6021	0.5635	0.5740	0.8150
80	0.6902	0.5548	0.5602	0.8958
100	0.5715	0.5478	0.5572	0.7841

The traditional recommendation model does not add auxiliary information and only uses a sparse scoring matrix for scoring prediction, and the effect is relatively poor. The recommendation effect based on the deep neural network is better because the side information is added to the model, but the side information is relatively sparse. The recommendation model based on the deep neural network uses CNN to process text information, which makes full use of text information and also integrates it into the corresponding item features. It enriches the item data more effectively and also shows that the deep neural network structure can better obtain the features of auxiliary edge information. Therefore, the effect of recommendation models based on deep neural networks is relatively good.

4.3. Experiments on the Improved Deep Neural Network Recommendation Model. In order to test the influence of the recommendation length on the recommendation results, the length of the recommendation list is different in the experiment. The recall results of the model on different data sets are shown in Table 3.

Table 3 shows that the model performs better on dense data (ml-100 k) than on sparse data (ml-1 m). The model performs better on dense data because dense data contains



(a) (b)

Figure 6: Map of the recommendation model before improvement and a single recommendation algorithm on different datasets. (a) Map of a single recommendation algorithm. (b) Map of recommendation model based on deep neural network.

Table 3: Recall on different datasets.

Dataset	ml-100 k	ml-1 m	ml-10 m	Amazon
50	0.16	0.08	0.07	0.17
100	0.30	0.21	0.18	0.35
150	0.35	0.28	0.22	0.40
200	0.39	0.37	0.34	0.45
250	0.47	0.45	0.41	0.51
300	0.50	0.58	0.52	0.54

more information, which alleviates the problem of data sparseness to a certain extent.

The performance of the two models is evaluated using three evaluation measures, RMSE, Recall, and MAP. The datasets are the previous 4 datasets. The generated recommendation list is 50 characters long, and Figure 7 illustrates the experimental results based on the average of five trials.

According to the experimental results, as shown in Figure 7, the RMSE of the deep neural network recommendation model is decreased in comparison to the recommendation model before improvement, and the Recall and MAP on the four datasets combined with the improvement of the rating matrix and user-item attributes are improved. It demonstrates that deep learning can improve the effectiveness of recommendations when combined with the rating matrix, user, and item data. Denoising autoencoder processing of the sparse rating matrix and side information can acquire deeper potential characteristics of the data and deliver more precise recommendations.

Finally, the influence of the number of hidden layers in the network on RMSE is verified. In this experiment, the number of hidden layers is set to 0–5, respectively. The experimental results are shown in Figure 8.

As seen in Figure 8, the RMSE value is lowest when the network's hidden layer count is set to 2. The value does not decrease as the number of concealed layers rises. However, as the number of layers is increased, the RMSE value also rises, leading to overfitting. The hidden number in the experiment is set to 2, taking into account the fact that each additional layer in the neural network model will make the process more complicated and make it more challenging to change parameter values.

According to the above experiments, it can be known that the improved recommendation model is simple and effective and has good practicability and computability for representation based on neural networks. This paper mainly focused on the recommendation algorithm based on neural networks and then introduced the use of neural network methods before and after improvement to realize the recommendation algorithm. Then it designed and implemented experiments according to these two algorithm models to obtain more practical experiment results.

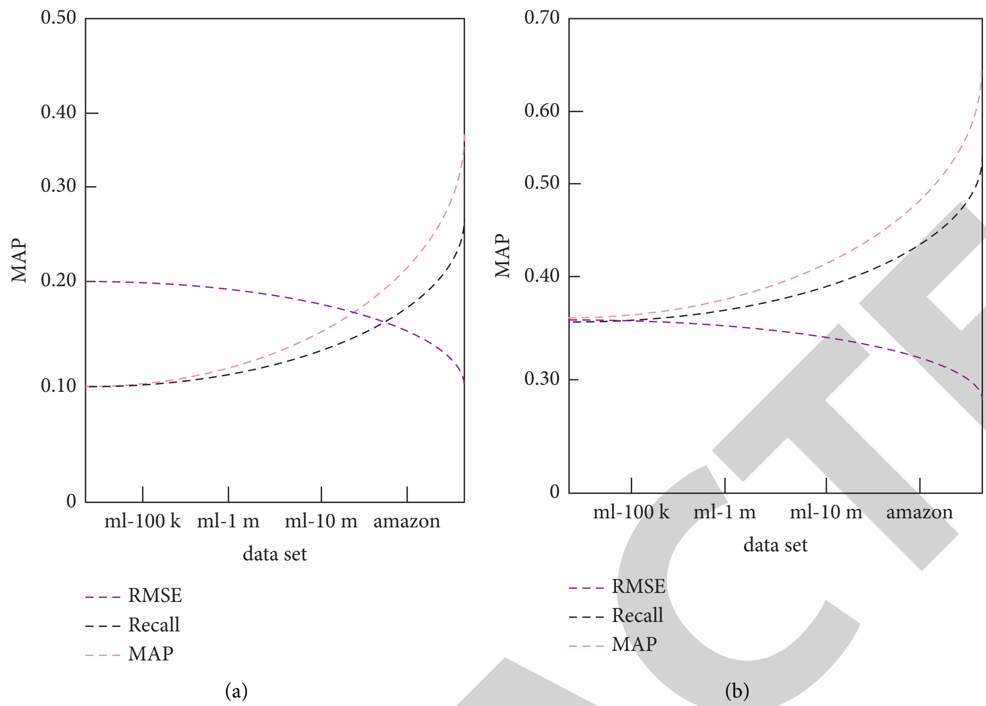


Figure 7: Comparison of different indicators of the deep neural network recommendation model before and after improvement. (a) Comparison of different indicators of the recommendation model before improvement. (b) Comparison of different indicators of the recommendation model after improvement.

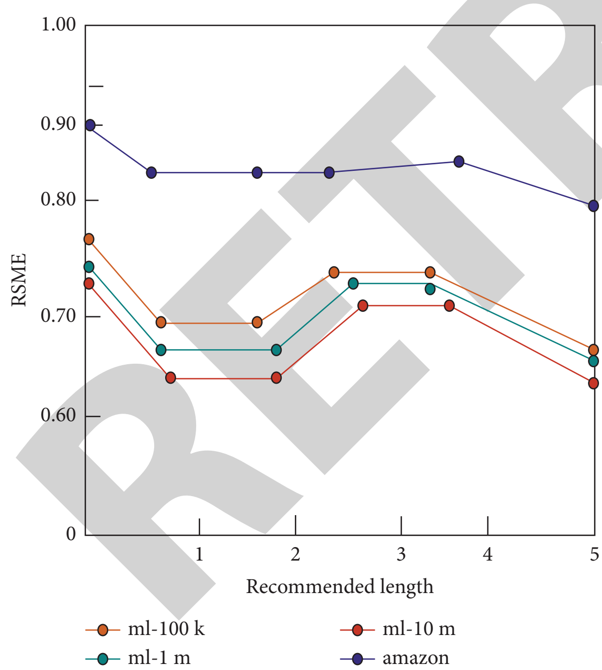


Figure 8: Effect of the number of hidden layers on RMSE.

5. Conclusion

The popularization and promotion of Chinese martial arts is an important cultural basis for improving people's unity and activating the spirit of martial arts culture. However, in recent years, the promotion of martial arts has been facing huge problems. Emei Martial Arts attaches great importance to the inheritance form of "master and apprentice." Even though Emei Martial Arts has been passed on to the greatest extent in a complete and orderly manner, some schools of Emei Martial Arts are still stuck in their own way because of their vertical characteristics, which limits the breadth and depth of their dissemination. Neural networks can better understand item characteristics, previous encounters between consumers, products, and user requirements. A deep neural network recommendation model and an upgraded deep neural network recommendation model were suggested in this paper based on these findings. On the basis of the recommendation algorithm, which attempts to enhance the algorithm's effect on recommendations, a better deep neural network recommendation model is created. To demonstrate the value of the algorithm suggested in this article, the paper carried out corresponding experiments in the experiment and evaluated the models of the two algorithms in different data sets and with three evaluation indicators. Finally, it found that an improved deep neural network recommendation model algorithm is higher than that of the preimproved recommendation model. Various errors are lower than those of the preimproved recommendation model, which also shows that the improved deep neural network recommendation model has an ideal recommendation, and Emei martial arts can be promoted. However, this paper only conducted experiments on four datasets, and the data obtained may not be very comprehensive. Hoping it will do better in future work.

Data Availability

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

This work was supported by the School-Level Educational Reform Project of the https://doi.org/10.13039/501100013079Neijiang Normal University (Project Nos. JK202059, YLZY201912-14, and 2021YB28).

References

[1] B. Moore, D. Dudley, and S. Woodcock, "The effect of martial arts training on mental health outcomes: a systematic review and meta-analysis," *Journal of Bodywork and Movement Therapies*, vol. 24, no. 4, pp. 402–412, 2020.

[2] J. H. Kwak and D. H. Yoo, "Martial art as media culture: movie & soup opera," *Korean Journal of Sports Science*, vol. 27, no. 2, pp. 165–175, 2018.

[3] H. L. Zhang, H. J. Zhang, and X. T. Guo, "Experimental study on Taijiquan exercise improving university students' cognitive function," *Cognitive Systems Research*, vol. 52, no. DEC, pp. 591–595, 2018.

[4] H. He, F. Gang, and C. Jinde, "Robust state estimation for uncertain neural networks with time-varying delay," *Journal of Jishou University (Natural Sciences Edition)*, vol. 19, no. 8, pp. 1329–1339, 2019.

[5] H. F. Yang, K. Lin, and C. S. Chen, "Supervised learning of semantics-preserving hash via deep convolutional neural networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 40, no. 2, pp. 437–451, 2018.

[6] S. Mei, A. Montanari, and P. M. Nguyen, "A mean field view of the landscape of two-layer neural networks," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 115, no. 33, Article ID E7665, 2018.

[7] L. F. Wang, H. Wu, D. Y. Liu, D. Boutat, and Y. M. Chen, "Lur'e Postnikov Lyapunov functional technique to global Mittag-Leffler stability of fractional-order neural networks with piecewise constant argument," *Neurocomputing*, vol. 302, no. AUG.9, pp. 23–32, 2018.

[8] P. Yin, S. Zhang, J. Lyu, S. Osher, Y. Qi, and J. Xin, "BinaryRelax: a relaxation approach for training deep neural networks with quantized weights," *SIAM Journal on Imaging Sciences*, vol. 11, no. 4, pp. 2205–2223, 2018.

[9] Y. Cheng, D. Wang, P. Zhou, and T. Zhang, "Model compression and acceleration for deep neural networks: the principles, progress, and challenges," *IEEE Signal Processing Magazine*, vol. 35, no. 1, pp. 126–136, 2018.

[10] P. Khosravi, E. Kazemi, M. Imielinski, O. Elemento, and I. Hajirasouliha, "Deep convolutional neural networks enable discrimination of heterogeneous digital pathology images," *EBioMedicine*, vol. 27, no. C, pp. 317–328, 2018.

[11] S. I. Venieris, A. Kouris, and C. S. Bouganis, "Toolflows for mapping convolutional neural networks on FPGAs: a survey and future directions," *ACM Computing Surveys*, vol. 51, no. 3, pp. 1–39, 2019.

[12] P. Cao, W. Xia, M. Ye, J. Zhang, and J. Zhou, "Radar-ID: human identification based on radar micro-Doppler signatures using deep convolutional neural networks," *IET Radar, Sonar & Navigation*, vol. 12, no. 7, pp. 729–734, 2018.

[13] M. Atzmon, H. Maron, and Y. Lipman, "Point convolutional neural networks by extension operators," *ACM Transactions on Graphics*, vol. 37, no. 4, 12 pages, 2018.

[14] Y. Luo, T. Xu, and Z. Xu, "Recommended method study based on incorporating complex network ripple net," *Xibei Gongye Daxue Xuebao/Journal of Northwestern Polytechnical University*, vol. 39, no. 5, pp. 1070–1076, 2021.

[15] H. Yao and H. Zhang, "Improvements of scaling method recommended by ITTC at a lower Reynolds number range," *Shanghai Jiaotong Daxue Xuebao/Journal of Shanghai Jiaotong University*, vol. 53, no. 1, pp. 35–41, 2019.

[16] X. M. Chen, Y. Li, Z. G. Zhao, T. Ma, and R. Wang, "General method to obtain recommended tilt and azimuth angles for photovoltaic systems worldwide," *Solar Energy*, vol. 172, pp. 46–57, 2018.

[17] Z. Jiang, Y. Wang, H. Zhong, and N. Meng, "Automatic method change suggestion to complement multi-entity edits," *Journal of Systems and Software*, vol. 159, Article ID 110441, 2020.

[18] K. C. Kim, J. B. Seo, K. B. Kim, and J. S. Yoo, "Rhabdomyolysis of the long head of the triceps brachii in a female adolescent after martial arts," *Journal of Arthroscopy and Joint Surgery*, vol. 7, no. 2, pp. 87–90, 2020.

[19] D. S. Kermany, M. Goldbaum, W. Cai et al., "Identifying medical diagnoses and treatable diseases by image-based deep learning," *Cell*, vol. 172, no. 5, pp. 1122–1131, 2018.

[20] M. Hillier, L. Sutton, L. James, D. Mojtahedi, N. Keay, and K. Hind, "High prevalence and magnitude of rapid weight loss in mixed martial arts athletes," *International Journal of Sport Nutrition and Exercise Metabolism*, vol. 29, no. 5, pp. 512–517, 2019.

[21] Z. Lv, Y. Li, H. Feng, and H. Lv, *Deep Learning for Security in Digital Twins of Cooperative Intelligent Transportation Systems*, IEEE Transactions on Intelligent Transportation Systems, New York, USA, 2021.

[22] Y. Zhao, H. Moayedi, M. Bahiraei, and L. Kok Foong, "Employing TLBO and SCE for optimal prediction of the compressive strength of concrete," *Smart Structures and Systems*, vol. 26, no. 6, pp. 753–763, 2020.

[23] A. Chc, A. Fs, B. Fjh et al., "A probability density function generator based on neural networks," *Physica A: Statistical Mechanics and Its Applications*, vol. 541, 2020.

[24] O. I. Khalaf, C. A. T. Romero, A. Azhagu Jaisudhan Pazhani, and G. Vinuja, "VLSI implementation of a high-performance nonlinear image scaling algorithm," *Journal of Healthcare Engineering*, vol. 202110 pages, Article ID 6297856, 2021.