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Retraction

Retracted: Research on Deep Learning Algorithm in Cultural and Creative Product Design

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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] W. Liu, F. Kou, and H. Huang, "Research on Deep Learning Algorithm in Cultural and Creative Product Design," *Scientific Programming*, vol. 2021, Article ID 3212882, 15 pages, 2021.

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Research Article

Research on Deep Learning Algorithm in Cultural and Creative Product Design

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Cultural and creative design is a new design mode based on the Internet platform, which gathers the design wisdom of the public and provides online solutions for design tasks. Evaluation indicators are used to score cultural and creative design schemes that require manual construction of an evaluation matrix, which makes the evaluation efficiency very low and increases the product design cycle. Therefore, based on the deep belief network of cultural creation, the method of constructing the evaluation model of the scheme is designed in this paper. According to the characteristics of the deep belief network, the k-medoids clustering method is adopted, and the clustering key value k is set. Meanwhile, the clustering result is calculated, and k central point elements are obtained. Moreover, project the central point elements back to the cultural and creative design plan to obtain the characteristic plan, and use manual evaluation to calculate the comprehensive score. Besides, the feature scheme data and the data simulation formula are used to construct the training set of the deep belief network, which are used to train the evaluation model of the deep belief network to solve the problem of the length of time that requires a large amount of manual evaluation to construct the output of the training set. In addition, according to the number of evaluation indicators, the number of nodes in the input layer of the deep belief network is determined to define the initialization method of network weights and biases, formulating experimental procedures to determine the optimal network structure. In the simulation experiment, through the test analysis of the comparison model, the function synchronization rate in this paper is 4.2% better than that of the comparison method. After multiple iterations, the test effect is 7 times higher than that of the comparison method, realizing the optimal evaluation of the design schemes that have not been manually evaluated in the same design scheme set.

1. Introduction

In recent years, the term cultural and creative products have repeatedly appeared in people's sight, and the new trend of fashionable life has been felt. Meanwhile, the creativity and design of cultural and creative products at domestic and foreign countries are constantly increasing. Therefore, the design of cultural and creative products is combined with relevant theoretical knowledge, design practice, research, and specific themes. In addition, aiming at how to make cultural and creative products better integrate with culture and the commercial market, ideas are proposed in this paper, hoping to attract others and give some inspiration to the design and development of cultural and creative products [1].

The experience value of cultural and creative products can not only meet consumers' material needs, but more importantly, they can meet their psychological needs. Moreover, cultural and creative products not only possess the general characteristics of ordinary commodities, but also possess cultural, regional, commemorative, practical, and contemporary characteristics [2]. Therefore, excellent cultural and creative products not only have the external form of artistic appreciation, but also can bring pleasant feelings to the audience through the appreciation of the inner spirit.

The research and design of cultural and creative products can connect culture and people. The old objects and life scenes are the source of design, and cultural customs are the core of design. Through fashionable and trendy cultural and creative products, interaction with young groups can be

achieved in modern society, promoting the dissemination and promotion of culture [3]. What is more, research and practice provide reference for the design and innovation of cultural and creative products, which have practical foundation and reference value. The regional cultural elements are rich in various forms, only part of which carries information related to the theme. Therefore, cultural and creative products will ultimately be materialized and visualized, and typical regional cultural elements with strong symbolic sense and clear forms should be first selected [4].

The choice of the design method and how to use it in the design of cultural and creative products are particularly important, which provides direction for how to reflect the cultural and artistic, regional, and national characteristics of cultural and creative products. Therefore, it is clearly recognized that product innovation is both the purpose and means of cultural and creative design, which is at the core of cultural and creative product activities. Meanwhile, it develops ideas for the design of cultural and creative products [5].

At present, the deep learning method has made great progress in data classification, fitting, regression, and prediction, especially in image recognition and reconstruction, speech recognition, and other fields [6]. In the process of data analysis using the deep learning model, it is mainly divided into three stages: data preprocessing, model structure training, and model testing and optimization, and each stage will affect the results of data analysis. In the aspect of deep learning network application, the test and optimization of model structure has become the main research field of many scholars, including proposing better adaptive network structure, such as Gaussian–Boltzmann machine, and proposing new model training methods, such as using the simulated annealing algorithm to optimize network structure parameters. These methods effectively improve the accuracy of model data analysis and provide a reference for subsequent research. Chen [7] divided product design into two target optimization problems of design and manufacturing through concurrent product and process design and proposed a satisfaction index to guide the selection of schemes with the help of the minimum and geometric average operators as the baseline. Besides, the comprehensive satisfaction of the two teams is calculated based on game theory. Vairaktarakis [8] adopted the quality house of product function (QFD) to consider the demand information of all customers and determined the combination of new products to meet the expected constraints and match or exceed the performance expectations of all customers in the target market.

For the cultural and creative design scheme, many designers participate in the design, which makes the data volume of the scheme large. At the same time, due to the consistent design goals, the data of cultural and creative design scheme also have the characteristics of strong data similarity [9]. The input of cultural and creative scheme data for deep learning network training is a part of the decision matrix of cultural and creative design scheme set, and the output is the comprehensive design result that must be calculated by the design team and combined with the weight of each index, which makes the manual work still very heavy.

In order to solve the problem of time-consuming for deep learning network to prepare training data set, the clustering method is used to analyze the data distribution law of cultural and creative design scheme, so as to reduce the labor time and reasonably construct training set to speed up the efficiency. This paper mainly studies the evaluation methods of the cultural and creative design schemes in the result output part of the cultural and creative design and studies the evaluation index selection and weight calculation methods of the cultural and creative design schemes. Moreover, the analytic hierarchy process is used to build a hierarchical structure for the cultural and creative program, and the evaluation index system is determined to obtain the vector representation of the cultural and creative design program. Besides, construct a judgment matrix, calculate the allocation matrix of index level and subcriterion level in turn, and check the consistency.

Structure of this paper is organized as follows:

(1) In Section 1, the research content, innovations, and organizational structure to be carried out are introduced in this paper.

(2) In Section 2, related work is introduced.

(3) In Section 3, the clustering model of the training set of the cultural and creative design scheme of the deep network is designed.

(4) In Section 4, the evaluation method of cultural and creative design plan is designed.

(5) In Section 5, experiments verify the research results proposed in this paper.

(6) Finally, summarize the full text and look forward to the future work.

The main innovations in this paper are as follows:

(1) The evaluation indicators are used to model the consistency of cultural and creative design schemes, which is conducive to data analysis of the deep belief network.

(2) According to the data characteristics of cultural and creative design plans, a deep belief network evaluation model is constructed, and the deviation standardization method is used to preprocess the data set of cultural and creative design plan.

(3) An evaluation method of cultural and creative design schemes using clustering is proposed, and the k-medoids clustering method is used to cluster the cultural and creative design plan data.

2. Related Work

In this paper, related technologies are introduced from the technical aspects of deep learning and restricted Boltzmann machines.

2.1. Deep Learning. With the vigorous development of the Internet big data, the research of deep learning has gradually become a mainstream trend and applied to various scenes in life [10].

The main network structures of deep learning models include auto-encoders, deep belief networks, and convolutional neural networks. Among them, the automatic encoder encodes and decodes the original data signal, which can be used for data noise reduction and data dimensionality reduction according to the number of hidden layers and the number of hidden layer nodes. Moreover, the deep belief network is composed of multiple restricted Boltzmann machines, which has a wide range of applications in the field of processing data classification. Since it also has the characteristics of fast convergence, it can also be used to initialize the structural parameters of the neural network to shorten training time. In addition, convolutional neural networks are often used in target detection and face recognition due to their huge advantages in image processing [11].

When deep belief network is used as the parameter initialization of neural network structure, it has the characteristics of fast training speed and not easy to fall into local extreme value. Therefore, the deep belief network is used in this paper to initialize the parameters of the evaluation network structure, and then the backpropagation algorithm is adopted to adjust the error of the model layer by layer. Finally, the scoring results of the cultural and creative design of the evaluation model are applied to making predictions [12].

2.2. Restricted Boltzmann Machine. The Boltzmann machine has a hidden layer and an input layer; the nodes between the layers are connected one by one, and the nodes in the layer are connected to each other. Due to the characteristics of the node connection in the layer, the time consumption in the training process is greatly increased, which brings difficulties to the use of the maximum likelihood method to train the network model structure [13]. Moreover, in this model, the connection between the nodes in the visible layer and the hidden layer is cancelled, and only the interlayer nodes are connected, which solves the problem of difficult training and is widely used. In addition, the restricted Boltzmann machine is a two-way undirected graph model, which consists of a visible layer v and a hidden layer h. What is more, the nodes between the visible layer and the hidden layer are connected one by one. The nodes in the layers are not connected, and the simplified structure of RBM is shown in Figure 1.

The restricted Boltzmann machine is a probability graph model that satisfies the Boltzmann distribution and the definition of the thermodynamic energy function. If a restricted Boltzmann machine has n visible layer nodes and m hidden layer nodes, the vector v can be used to represent the visible layer node, and the vector h can be used to represent the hidden layer node. For the restricted Boltzmann machine, the energy function $E(v, h|\theta)$ is defined as

$$E(v, h|\theta) = -\sum_{n}^{i=1}\sum_{m}^{j=1} w_{ij}v_i b_i b_i - \sum_{n}^{i=1} a_i v_i - \sum_{m}^{j=1} b_j h_j, \qquad (1)$$

where $\theta = \left\{w_{ij}, a_j, b_{ij} 1 \le i \le n, 1 \le j \le m\right\}$ is the parameter of the restricted Boltzmann machine and w_{ij} refers to the weight between the visible node i and the hidden node j. b_i is the bias of the visible node i, andb_j is the bias of the hidden node j [14].

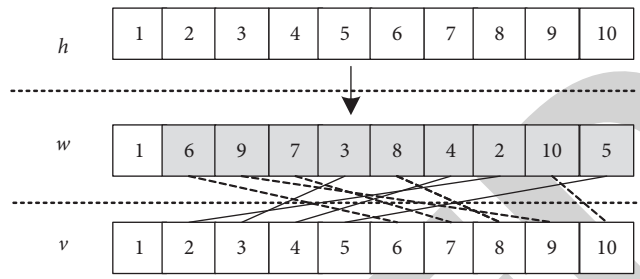

Figure 1: Structure of the restricted Boltzmann machine.

3. Clustering Model of Training Set of Cultural and Creative Design Schemes Based on Deep Network

According to the problems of sampling and reconstruction work in traditional cultural and creative design schemes, a training set clustering model of deep network is designed, and the model structure and training method are optimized.

3.1. Insufficiency of Cultural and Creative Design Schemes. The deep learning network model for cultural and creative design scheme can achieve a high degree of accuracy under the condition of sufficient training data preparation and can improve the work of cultural and creative design scheme, but this method also faces the following two problems:

(1) The training of deep learning network can be divided into two steps: pretraining and optimization [8]. For the pretraining, the training of deep learning network model requires t cultural and creative design schemes $P_i(i = 1, 2, \ldots, t)$ as the input v of deep learning network. The contrast divergence method is used for data sampling and reconstruction. Finally, the training results of each RBM and the parameter values of each layer are obtained. The overall structure of deep learning design scheme is shown in Figure 2.

In the process of pretraining, the data are obtained after the unified index screening and the calculation of index weights at all levels, which takes less time and is relatively easy to obtain. In the optimization stage of network structure parameters, it is necessary to use the design result K of each cultural and creative design scheme to input back from the deep learning network and use the backpropagation algorithm of neural network training to adjust the error of the whole network structure parameters, so as to optimize the data analysis ability of the model [15]. In the optimization stage, the data used must be screened based on indicators to get the results of each cultural and creative design scheme. The time consumption depends on the number of cultural and

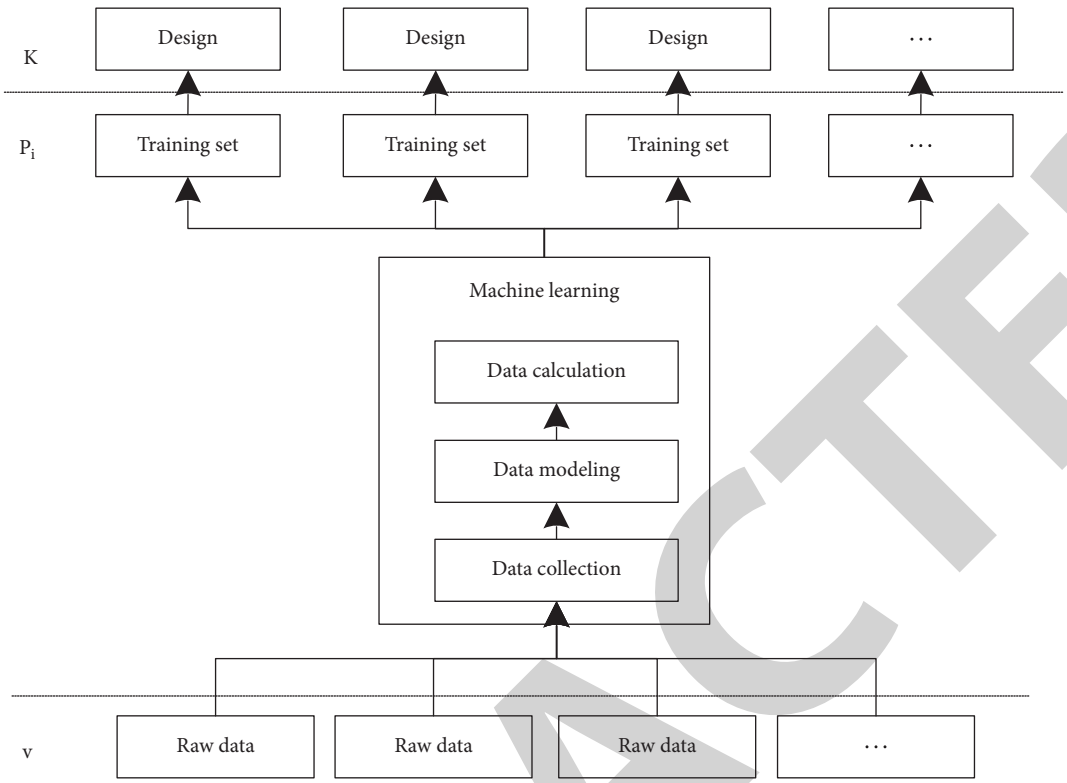

Figure 2: Overall structure of the deep learning design scheme.

creative design schemes used for training and the time taken for a single cultural and creative design scheme to be screened by the design team. It is relatively difficult to obtain the data, which greatly reduces the efficiency of the whole model [16].

(2) Randomness of training data selection: in the process of adopting the deep learning network cultural and creative design scheme, the cultural and creative design scheme selected as the training data set is randomly selected, without considering the distribution law and similarity degree of the cultural and creative design scheme data, which makes the training of the model have a strong contingency; for the cultural and creative design scheme with high similarity, it has the feature of repeated manual. Moreover, it will reduce the model efficiency, resulting in great errors in the data of cultural and creative design schemes with large differences [17].

Therefore, it is necessary to improve the selection process of training data of deep learning network, so as to improve the accuracy of the model and the efficiency of training data preparation, and solve the problem of long time.

3.2. The Clustering Model of the Training Set of Cultural and Creative Design Schemes. For a large number of data, clustering is a data mining method to obtain data distribution rules. For the cultural and creative design scheme under the same cultural and creative design, due to the same design objectives and the same defined index system, the similarity between the data is more likely [18]. This paper analyzes the cultural and creative design schemes in a unified dimension by using the clustering method and divides them into H clusters; then it takes the central data of each cluster as the feature scheme to obtain the criteria, and the structure of the clustering scheme is shown in Figure 3.

Although the method of feature scheme improves the efficiency, it reduces the number of training concentration schemes of the deep learning model, which is not conducive to the training and testing of the model. In order to train the model with accurate results, the training set should be expanded. Because of the strong randomness of the design scheme, the normal distribution random number is used to fit the original data fluctuation space. The training set of cultural and creative design scheme for training and the test set of cultural and creative design scheme for testing are reasonably constructed as the data input of the deep learning model [19].

The following three steps can be used to cluster the training set of cultural and creative design schemes:

(1) Cluster analysis of cultural and creative design schemes: for all cultural innovation design scheme $P_i\,(i = 1, 2, \ldots, t)$, if its index number is k, it is projected into the k-dimensional space to obtain a set of data point clouds of cultural innovation design scheme. Set a reasonable cluster number H, use the K-means clustering algorithm to perform clustering calculation on the data of cultural and creative clustering design scheme, and get the center of each cluster [20].

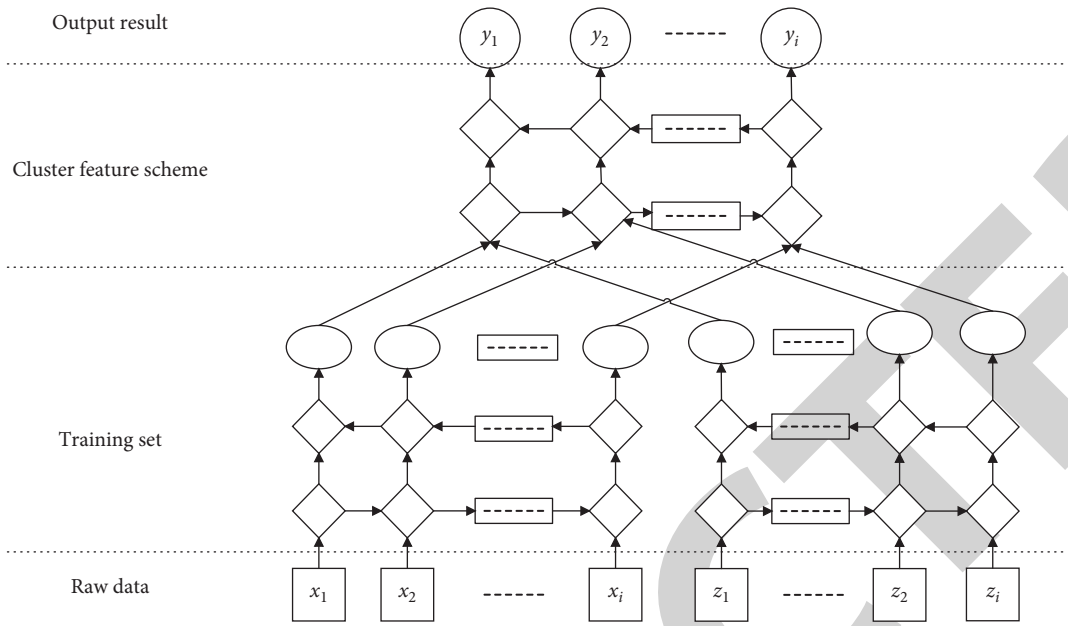

Figure 3: Clustering scheme based on the deep learning network model.

(2) Feature scheme and construct training set: take the center of the cluster group, calculate with the European distance calculation equation, and construct the preliminary set Pre by using the distance of all schemes within the group and the minimum scheme. The preliminary set is used as the sample for technical guidance, the matrix is obtained, and the comprehensive score of the feature scheme is calculated based on the weight distribution results. The value characteristics of each index were analyzed, and the training set of deep learning network was constructed by using the data simulation equation [21].

(3) Training and optimization of the deep learning network model: the deep learning network model is used as the model, the constructed training set is used to train the deep learning network model, and then the original cultural and creative design scheme data are used as the test set to test the model and verify the training effect of the simulation training set on the model [22].

3.3. Cultural and Creative Design Plan Data Set Preprocessing. For any cultural and creative design scheme $P_t = (\alpha_{i1}, \alpha_{i2}, \ldots, \alpha_{ik})$ taken from the set of cultural and creative design schemes $S = \{P_1, P_2, \ldots P_i \ldots P_N\}$, it is assumed that after the evaluation of the scheme based on the evaluation index, the score obtained is y_t. Meanwhile, if t cultural and creative design schemes $p_t\,(t = 1, 2, \ldots, n)$ are used as the input V of the deep belief network, and the scoring resulty_t is used as the output of the deep belief network, the network model will be trained to obtain the evaluation rule of the scheme, and the trained model can be used to evaluate the unevaluated cultural and creative design plan $p_i\,(i = t + 1, t + 2, \ldots, t + n)$, so that the scoring result y_i^o of the deep belief network model can be obtained. As long as y_i^o meets the scoring error requirements, the evaluation result can be used to replace the manual evaluation result, reduce the evaluation work of cultural and creative design schemes, and improve the evaluation efficiency [23].

Due to the limitation of the activation function sigmoid in the restricted Boltzmann machine, the value range of each node of the input layer v is [0, 1]. In addition, to reduce the computational cost of the RBM training reconstruction process and achieve better training results, it is necessary to perform normalization processing before inputting the cultural and creative design plan data into the model, so that the model algorithm can run better and achieve the desired effect [24].

Before normalizing the data of the cultural and creative design plan, it is necessary to consider whether to reduce the dimensionality of the cultural and creative design plan data to remove the secondary features and select the main features to make the evaluation results of the model better. Nowadays, data dimensionality reduction is mainly selected by manual feature extraction and principal component analysis dimensionality reduction [25]. Moreover, for data whose dimensionality fc is more than hundreds or thousands, using principal component analysis is a very effective method to reduce dimensionality. Besides, for the cultural and creative design data, since the dimension of the design data is controlled by the number of evaluation indicators, and the primary and secondary relationship of the features has been considered in the selection process of the evaluation indicators, the dimensionality reduction and non-dimensionality reduction can be selected according to the specific situation [26].

Nowadays, the normalization method for mapping data to the interval of [0, 1] is the min-max standardization method, which has also become the dispersion

standardization method. This method uses the maximum and minimum values of the data under the unified index to linearly transform all the data and map them to the target interval, which can also be scaled according to the needs of the interval [27]. If the evaluation index parameter α_{ij} of any cultural and creative design plan p_i, whose maximum value in the sample data set is $\alpha i_{j\max}$, the minimum value is $\alpha_{ij\min}$, and the standardized evaluation index parameter is α'_{ij}, using the deviation standardization method, the calculation method of a'_{ij} will be

$$a'_{ij} = \frac{a_{ij} - a_{ij\min}}{\alpha_{ij} + na_{ij}}. \quad (2)$$

For all evaluation indicators α_{ij}, after normalized with the scoring results, if $v_i = \alpha'_{ij}$, the visual layer input $v = (v_1, v_2, \ldots, v_k)$ and output y'_i of the deep belief network can be obtained.

3.4. Evaluation Model Network Structure and Parameter Selection. The construction of a deep neural network mainly includes the following: the number of network layers and nodes of each layer, the initial structure parameter value of the network, the learning rate and momentum of weight updating, the number of iterations of reconstruction, and BP [28].

For the deep neural network model used for the evaluation of cultural and creative design schemes, the number of visual layer nodes v is equal to the number of evaluation indexes, and the value is K. The number of nodes in the output layer is equal to the number of design results, with the value of 1. According to the characteristics of deep neural network, the number of hidden layers is small, and the effect of feature extraction is not different from the function of the neural network. Too many hidden layers will lead to a large deviation between the reconstructed data of the later layers and the original data, resulting in data distortion. For the value of nodes of each hidden layer, there are three methods: decreasing layer by layer, increasing layer by layer, increasing then decreasing first, and decreasing then increasing first. Since there is only one design result of the cultural innovation design scheme and the number of output nodes is small, the value method of decreasing then increasing and increasing layer by layer cannot be adopted. Therefore, the layers of the deep neural network model need to be analyzed through experiments to determine the optimal choice [29].

The initial value of network structure parameters will have an influence on the result of scheme evaluation, and the reasonable choice of parameter initialization method is conducive to improving the accuracy of scheme evaluation [30]. At present, there are three methods to initialize structural parameters of the deep neural network, namely, Xavier initialization method, Gaussian initialization method, and uniform random initialization method. The specific initialization table is

(1) The Xavier initialization method: $w \sim U\left(-\sqrt{(6/n_{\text{in}} + n_{\text{out}} + 1)}, \sqrt{(6/n_{\text{in}} + n_{\text{out}} + 1)}\right)$, where n_{in} and n_{out} represent the number of neurons in the input layer and output layer connected by the weight and U represents the uniform distribution.

(2) Gaussian initialization method: $w \sim N(0, 0.01)$, N is the Gaussian distribution.

(3) Uniform random initialization: $w \sim U\left(-\sqrt{(1/d)}, \sqrt{(1/d)}\right)$, where d represents the number of input layer neurons connected by weights.

Because the data distribution of cultural and creative projects is similar to the Gaussian distribution, the Gaussian initialization method is used to initialize the network structure parameters. When using the contrast divergence method to update RBM weights, learning rate and momentum are two key training parameters, which determine the update rate of network structure weights, and can accelerate the speed of model convergence and training. In the selection process of learning rate, if the learning rate is too large, it will cause the solution of the parameters to diverge near the best point, resulting in the increase of training error, the weight will be too large, and the evaluation effect of the model is not ideal; although the selection of small learning rate can effectively avoid the above problems, it will also lead to slow convergence speed and longer training time of the evaluation model [31]. Adding momentum element in the process of training can make each weight update not only related to the gradient, but also related to the last updated weight, so as to improve the evaluation effect. Generally, the learning rate is between 0 and 0.1, and the momentum is below $0.5 \sim 0.8$.

Hinton proposes the contrast divergence method, and the reconstruction times of the constrained Boltzmann machine is generally 1, which can get good results. The iteration times of the backpropagation algorithm used in the structural parameter optimization process of the rating model can be obtained by the BP error convergence of the actual model [32].

3.5. Training Method of Evaluation Model. The training process of the deep neural network model for the evaluation of cultural and creative design schemes is shown in Figure 4.

(1) Preprocess the parameter, assigning a value to visual layer V. The range normalization method is used to preprocess all the cultural and creative evaluation schemes $P_1, P_2, \ldots, P_i, \ldots, P_N$ in the cultural and creative design scheme data set S, and the partially normalized cultural and creative design scheme $Pi(1 = 1, 2, \ldots, t)$ is used as the visual layer of the deep neural network model to input into the training network model; the Gauss initialization method is used to initialize the network structure parameter 0, in which the connection weight w and the visual layer offset a are used. The values of hidden layer bias b are all 0.1; the parameter learning rate is set to 0.1, the momentum p is set to 0.5, the number of RBM reconstruction is set to 5, and the number of BP reverse iteration is set to 500.

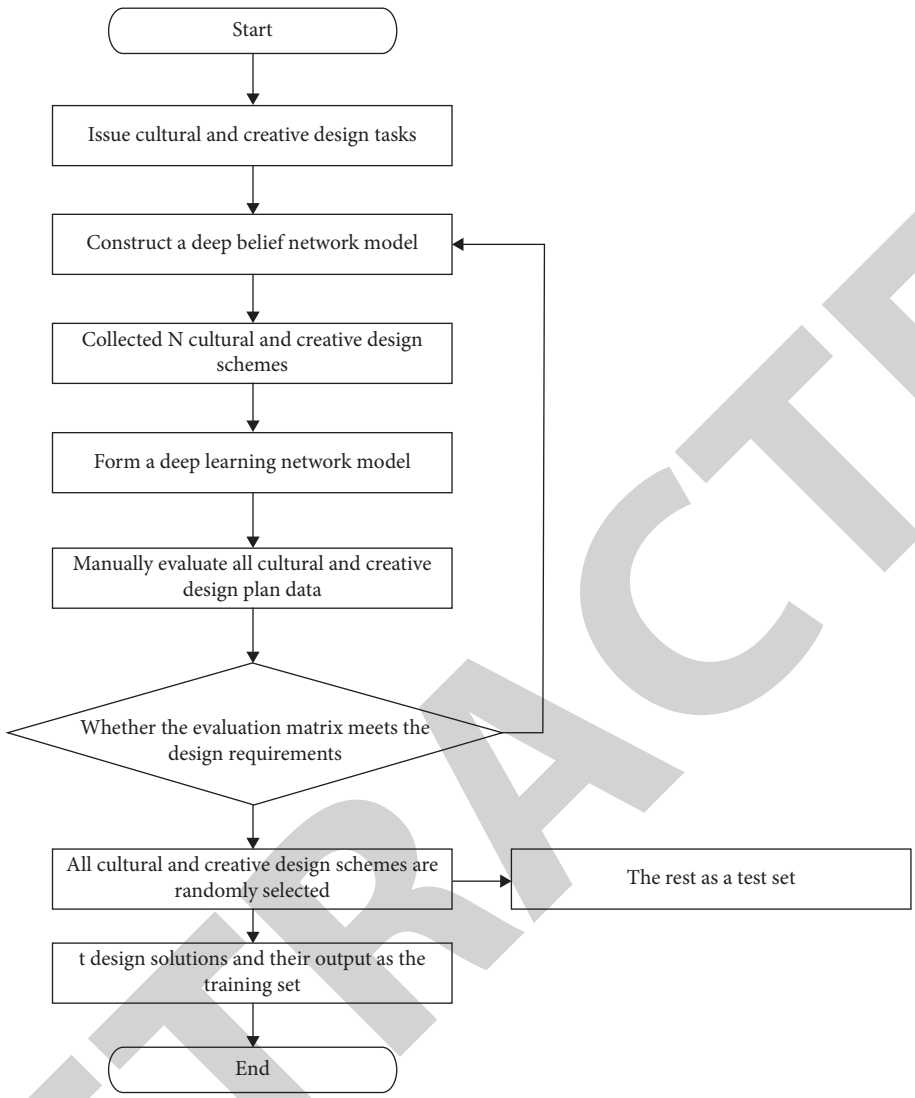

Figure 4: Cultural and creative design scheme process based on the deep learning network model.

(2) The hidden layer node value h is calculated. The activation probability $P(h_i = 1|v\colon 0)$ of hidden layer node h_i is calculated according to the following equation:

$$P(h_i = 1|v, \theta) = \text{sigma}\left(\sum_{n}^{i=1} w_{ij} v_i + b_j\right), \tag{3}$$

where θ is the activation function of sigmoid.

The value of the hidden layer node is determined by a randomly generated set of 0-1 random numbers. The value of the hidden layer node h distribution is obtained by judging the condition that the value is 1 or 0.

(3) Calculate and reconstruct visual layer v'. After calculating the value distribution result of the calculated hidden layer, equation (2) is used to calculate the value of each node of the visible layer, and the reconstruction is completed to obtain the value distribution h of the visible layer:

$$P(v_i = 1|h, \theta) = \sigma\left(\sum_{m}^{j=1} w_{ij} h_j + a_i\right). \tag{4}$$

(4) Calculate the weight update value. The adjusted values of various parameters are calculated according to the following equation:

$$\Delta w_{ij} \leftarrow \rho \cdot \Delta w_{ij} + \eta\left(P\left(h_j = 1|v\right) \cdot v - P\left(h_j - 1|v\right) \cdot v\right). \tag{5}$$

where ρ is the momentum and $\eta$is the learning rate.

(5) RBM is trained layer by layer. Record the calculated RBM structure parameters, and input the hidden layer h as the visual layer of the next restricted Boltzmann machine into the network structure. Use Step 2, Step 3, and Step 4 to calculate the structure parameters of the second restricted Boltzmann machine until all the structure parameters of the

restricted Boltzmann machine are calculated, and complete the pretraining process.

(6) Backpropagation algorithm optimization. The trained DBN is taken as a neural network with the same structure, and the structure parameters of each RBM are taken as the initial parameters of the neural network. The corresponding design result Y_i of the cultural and creative design scheme $P_i\,(i = 1, 2, \ldots, t)$ used for training is taken as the label, which is input in the output layer, and the BP algorithm is used for reverse training to adjust the parameter error of the whole structure.

(7) Test and evaluate the accuracy of the model. The untrained cultural and creative design scheme data $P_i\,(i = t + l, t + 2, \ldots, N)$ are tested to obtain the output design result y_i' of the deep training model. The y_i deviation degree of y_i' from the known manual evaluation result was calculated. If the deviation degree is within the allowable range, the training is completed; otherwise, the parameter structure is changed and the training is reconducted.

4. Evaluation Method of Cultural and Creative Design Plan

Clustering is to divide the data objects in the data space into different classes or clusters according to a unified standard, so that the similarity of data objects in the same class is as large as possible, and data objects that are not in the same cluster are as diverse as possible. After clustering, the data of the same category should be gathered together as much as possible, while the data of different categories should be separated as much as possible. Moreover, the clustering of cultural and creative design schemes can be described as follows: in the data space, N cultural and creative design schemes constitute the data set S, and the cultural and creative design scheme data point $P_i = (a_{i1}, a_{i2}, \ldots, a_{ik})$. Each attribute of P_i is numeric. In addition, the ultimate goal of clustering is to divide the data set S into H partitions $d_f\,(f = 12, \ldots, h)$. It is also possible that some data objects do not belong to any partition, and these are noise S. The union of all these divisions and noise is the data set S, and there is no intersection between these divisions, namely,

$$\begin{cases} S = D_1, \\ D_1 v_j = Q, \quad (i \neq j). \end{cases} \tag{6}$$

These divisions d_f are the clustering results of the cultural and creative design plan.

The number of evaluation indicators for cultural and creative design schemes is massive, and the total amount of design schemes is large. To make the results of clustering reflect the laws of cultural and creative design schemes, the clustering algorithm for cultural and creative design schemes should meet the following three requirements:

(1) Adopt clustering algorithms that can handle the same amount of cultural and creative design plan data sets. Some clustering algorithms can perform clustering well on smaller data sets with data objects within dozens of them. Sometimes to reduce the number of data objects to be processed, sampling methods are used. Sampling can improve the efficiency of clustering, which will also affect the results of clustering and even cause errors. Therefore, sampling methods should be adopted reasonably.

(2) The clustering method that is not sensitive to individual data has a good classification effect on the data distributed near the center of the class, but for the data far away from the center of the class, the clustering results are very different. For example, under different input orders, some data objects will be divided into different clustering groups with the help of the same clustering algorithm, which is not conducive to further analysis and processing. Therefore, the selected clustering algorithm should be able to obtain the same clustering results after clustering all the data.

(3) It must have the ability to process high-dimensional data. The data dimension of the cultural and creative design plan is determined by the number of evaluation indicators, and the number of evaluation indicators is more than 10. In addition, compared with two-dimensional data and three-dimensional data, the clustering of cultural and creative design schemes requires the use of clustering algorithms that can process high-dimensional data and analyze the distribution of data.

The k-medoids clustering algorithm is called the k-center point algorithm, which is an algorithm that uses the object closest to the center in the data object cluster to represent the forbidden algorithm. It is an improvement of the k-means algorithm. Moreover, the k-means algorithm uses the data centroid of each cluster to classify. Compared with noise and outlier data, a very large value will have a greater impact on the calculation result of the centroid. Meanwhile, the k-center point algorithm replaces the center of mass with the center point, which can effectively eliminate this effect. The processing process of the k-center point algorithm can be divided into the following four steps:

(1) Determine the number of clustered data clusters K, and initialize the center point. First determine the number of clustered data clusters K, and randomly select K cultural and creative design data points from the cultural and creative design data set $S = \{P_1, P_2, \ldots P_j, \ldots P_K\}$ as the initial center point.

(2) Divide the data points of all cultural and creative design schemes into clusters. For any cultural and creative design scheme $P_j \in S\,(j = 1, 2, \ldots, N)$, calculate the distance $d_f = \|p_j - D_f\|$ from p_j to each center point. If the distance $f = t$ obtains the minimum value $d_{\min}$ at time $f = t$, divide the data point p_j into the t-th cluster. Among them, the calculation of distance d_f adopts Euclidean distance, and its formula is

$$d_f = \left\| p_j - D_f \right\| = \left(\sum_{y=1}^{k} \left| P_{jy} - D_{fy} \right|^2 \right)^{1/2}. \quad (7)$$

(3) Calculate the square error criterion function E. After all the sample clustering of cultural and creative design schemes are completed, a unified criterion should be used to describe the excellence of the clustering results, namely, the compactness of the data clusters. What is more, the square error criterion E is the judgment index obtained by summing the distance squares from the currently selected center point to all sample points in the cluster. It can be considered that the smaller the value of E is, the more compact the cluster will be. When E achieves the minimum value, the center point at this time is the characteristic scheme. The calculation formula of the square error criterion is

$$E = \sum_{j}^{N} \left\| P_j - D_f \right\|. \quad (8)$$

(4) Update the center point and find the square error criterion function E until E takes the minimum value. The current center point D_f is arbitrarily taken from the cultural and creative design plan data set S, and its square error criterion function E is not necessarily the minimum value. Take data points from each cluster to update the center point, and repeat Steps 2 and 3 to obtain the value of the smallest square error criterion E in the cluster, and use this point as the new center point to recluster. Repeat the above steps until the new center point set is the same as the original center point set, and the algorithm terminates.

The center point plan of the final clustering result $D_1, D_2, \ldots, D_h$ is selected to construct the feature plan set $s' = \{p_1', p_2', \ldots, p_j', \ldots, p_h'\}$, and the feature plan set is used as the sample of learning evaluation rules for manual evaluation.

5. Simulation Experiment Analysis

Based on the evaluation method of cultural and creative design plan proposed in this paper, a customized cultural and creative design platform is developed. Taking the cultural and creative design plan as an analysis, the performance of the method in this paper is tested to evaluate the cultural and creative design plan in MATLAB.

5.1. Model Test Conditions. The software and hardware environment of the model test is shown in Table 1.

5.2. Training Data and Test Data of the Model. The analytic hierarchy process is used to construct a judgment matrix for the upper-level indicators and the lower-level indicators to calculate the weight of each evaluation indicator. The judgment matrix constructed for the upper-level indicators is

Table 1: Model testing hardware and software environment.

Item	Configuration	Model
Hardware configuration	CPU	i7-7700 HQ
	GPU	GTX 1050 Ti
	RAM	32 GB
	Hard disk	1T SSD
Software configuration	OS	Win 10 x64
	IDE	PyCharm
	Programming language	Python 3.5
	Deep learning framework	TensorFlow 1.11

$$A_1 = \begin{cases} 1 & 1 & 2 & 4 \\ 1 & 1 & 2 & 4 \\ \frac{1}{2} & \frac{1}{2} & 1 & 2 \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{2} & 1 \end{cases}. \quad (9)$$

The eigenvector of the judgment matrix is solved by the 1-order column average solution method, and T_i is obtained by accumulating each column first:

$$T_1 = \left(\frac{11}{4}, \frac{11}{4}, \frac{11}{2}, 11 \right). \quad (10)$$

After normalizing the columns of the judgment matrix A_i, the judgment matrix D of the type is obtained:

$$D = \begin{cases} \frac{4}{11} & \frac{4}{11} & \frac{4}{11} & \frac{4}{11} \\ \frac{4}{11} & \frac{4}{11} & \frac{4}{11} & \frac{4}{11} \\ \frac{2}{11} & \frac{2}{11} & \frac{2}{11} & \frac{2}{11} \\ \frac{1}{11} & \frac{1}{11} & \frac{1}{11} & \frac{1}{11} \end{cases}. \quad (11)$$

Accumulate the elements of each row, calculate the sum value, and get the eigenvector R:

$$R_1 = \left(\frac{16}{11} \frac{16}{11} \frac{8}{11} \frac{4}{11} \right)^T. \quad (12)$$

After normalization, the weight distribution matrix W_i of the superior index is obtained:

$$W_i = (0.3636, 0.3636, 0.1818, 0.0909)^r. \quad (13)$$

After calculating the weight distribution matrix, check the consistency of the judgment matrix A_i. Then, the judgment matrix and the weight distribution matrix are used

to calculate the characteristic root matrix of the judgment matrix A_i according to formulas (2)–(9):

$$AW_i = (0.8408, 0.8408, 1.6816, 0.3633)^r. \quad (14)$$

Then calculate the maximum characteristic root according to formulas (2)–(10) $\lambda_{\max} = 4$.

For the value of RI corresponding to each level of judgment matrix, when $n = 4$, $R_i = 0.89$, and $CI = 0, CR = 0 < 0.1$ can be obtained. Then the weight result of the superior evaluation index will be credible. With the help of the above method, construct the judgment matrices A_2, A_3, A_4, and A_5 for the secondary evaluation index, and calculate the weight distribution results W_2, W_3, W_4, and W_5 of the judgment matrix.

The judgment matrix A_2 constructed for the secondary evaluation index of the structural index is

$$A_2 = \begin{cases} 1 & 2 & 2 & 2 \\ 1/2 & 1 & 1 & 1 \\ 1/2 & 1 & 1 & 1 \\ 1/2 & 1 & 1 & 1 \end{cases} \quad (15)$$

The weight distribution matrix W_2 is calculated as

$$W_2 = (0.3333, 0.1667, 0.1667, 0.1667, 0.1667)^T. \quad (16)$$

Finally, the consistency test and summary of each judgment matrix are performed, and the final weight distribution results are calculated and summarized in Table 2.

After selecting the evaluation index and calculating the weight of the evaluation index on the collected 100 groups of cultural and creative design schemes, cluster analysis of the cultural and creative design schemes can be performed.

Matlab's tsne function is used to reduce the dimension of all cultural and creative design plan data to 2 dimensions for visual analysis, and the element dimension data are still used in the process of clustering to avoid distortion. The two-dimensional distribution of 100 groups of cultural and creative data schemes is shown in Figure 5.

The k-medoids algorithm is used for clustering analysis of the cultural and creative design plan data, and a different cluster number k is set. Meanwhile, the clustering result is analyzed by the elbow method to determine the optimal cluster number k. In addition, the elbow clustering uses sum of the squared errors (SSEs) to analyze the clustering results. The smaller the SSE is, the better the clustering results will be. When the value of k is larger, the value of SSE will become smaller, but as the number of classes increases, the change of the SSE value will change. When the value of k increases for the last time, the SSE decreases significantly, which is where the optimal value of k is located. Figure 6 shows the clustering SSE of the cultural and creative design scheme of the injection parts of the injection molding machine with the k value.

5.3. Specific Experimental Model Design. In order to verify the proposed model in this paper, approximating the model input variables x_1, x_2, x_3, x_4 and output response Y_1, Y_2, Y_3 contained between the low-order and high-order power function, trigonometric function, inverse trigonometric function, and exponential function elementary function, such as strong nonlinear mapping relations, can be done through the simplified design depth model CDMT01 cross validation method.

The shallow models CSMT02 and CSMT03 are designed as their comparison models. The shallow model CSMT02 has the same training conditions, functions, and the total number of hidden neurons of the network compared with the depth model CDMT01, but only the number of model layers is different. The shallow model CSMT03 has the same training conditions and the selection of neuron activation function compared with the shallow model CSMT02, but only the number of model layers is different. The number of neurons in the hidden layer of the model is increased to 2 times, and the specific superparameters of each model are shown in Table 3.

The reason why the depth model in the model test only contains CDMT01 and no other depth model is designed as a comparison model is as follows:

(1) One of the main roles of the depth model CDMT01 in model testing is to compare the performance of the shallow models CSMT02 and CSMT03 as comparison models and quantitatively show its comparative advantages;

(2) If the depth model CDMT01 can directly achieve great advantages only through the BP algorithm in model testing (which is difficult to achieve for most DNN models designed by other rules), then this itself can fully prove that the guiding theory of DNN model design in this paper is correct, scientific, and reasonable; otherwise the DNN model will not be successful. Compared with the shallow model with mature theory, the performance of the model and the convergence speed of the parameter training are superior.

5.4. Performance Comparison of Each Experimental Model. The Adam optimization algorithm is selected as the model training algorithm, and the test data set is used to test the current training effect and performance of the model after each iteration training. After programming and operation under TensorFlow, the training results of each model are shown in Table 4 and Figure 7.

In Figure 7, the synchronous approximation effect of each experimental model for the three test functions is observed: from the analysis in the degree of approximation of function fitting, shallow model CSMT02 after 10000 iterations training for test function Y_1 is relatively the best fitting effect.

The trend chart of adjusted R-square in each experimental model for the test data set during training is shown in Figure 8.

In Figure 8, all the green lines can quickly reach the highest point (the maximum value of adjusted R-square is 1) and keep close to 1, which shows that both the depth model

Table 2: Matrix weight distribution results.

Superior indicator	Weight	Secondary indicator	Weight	Comprehensive weight
C_1	0.35	B_1	0.34	0.11
		B_2	0.15	0.06
		B_3	0.15	0.06
		B_4	0.15	0.06
C_2	0.40	B_5	0.17	0.06
		B_6	0.17	0.06
		B_7	0.19	0.08
C_3	0.15	B_8	0.25	0.13
		B_9	0.25	0.13
C_4	0.10	B_{10}	0.42	0.14
		B_{11}	0.42	0.14

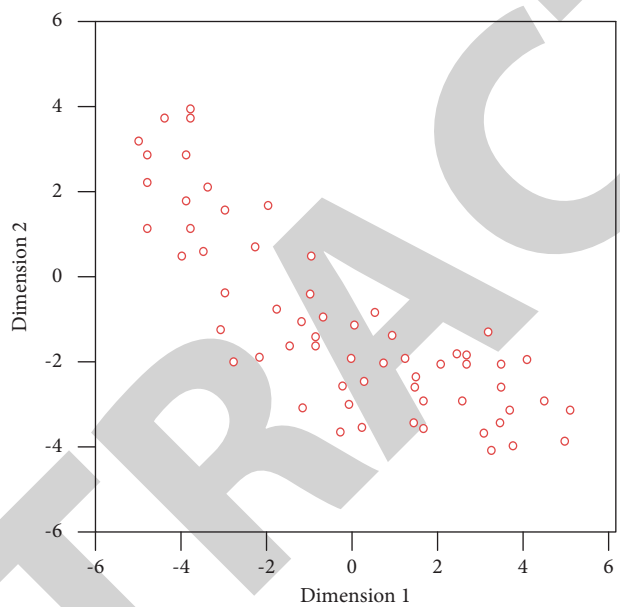

Figure 5: Two-dimensional distribution map of the cultural and creative design plan.

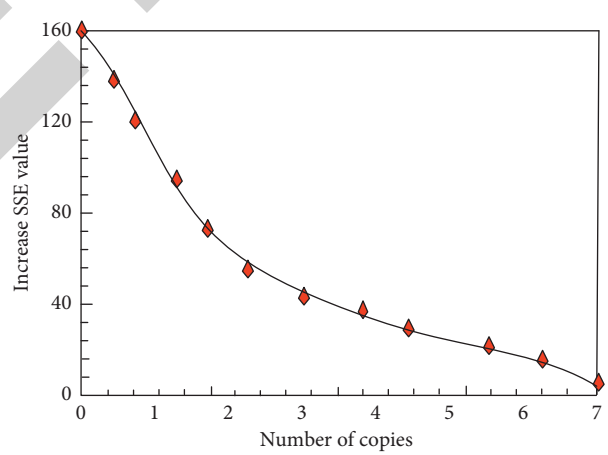

Figure 6: The clustering error squared sum (SSE) varies with the number of clusters (k).

and the shallow model have very good approximation effect for the test function Y_1.

The RMSE variation trend of the test data set during the CDMT01 training of the depth model is shown in Figure 9.

In Figure 9, in the training of approximation, the RMSE approximated by the model to each test function is only achieved after about 150 iterations. In the subsequent training process, the RMSE approximated by the model to each test

Table 3: Overview of experimental model hyperparameters.

Model	Model neuron number distribution	Distribution of neuron activation function in each layer of the model	Total hidden layer neurons
CDMT01	5-160-100-80-50-3	$a - ReLU - cr - ReLU - ReLU$	390
CDMT02	5-390-3	$a - ReLU$	390
CDMT03	5-780-3	$a - ReLU$	780

Table 4: Experimental models adjusted R-square training results for the model test set.

Network model	CDMT01	CDMT02	CDMT03
Neuron number distribution	5-160-100-80-50-3	5-390-3	5-780-3
Total hidden layer neurons	390	390	780
Y_1 test data	0.98154	0.97215	0.97678
Y_2 test data	0.98687	0.88356	0.51459
Y_3 test data	0.99994	0.84569	0.34586
Number of iterations	9900	9999	9999

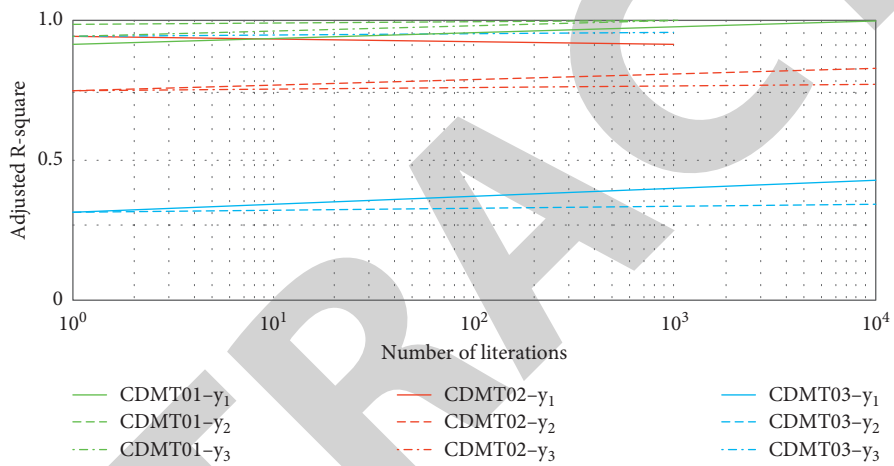

Figure 7: Changes in the adjusted R-square for the test set after the 9000th iteration training.

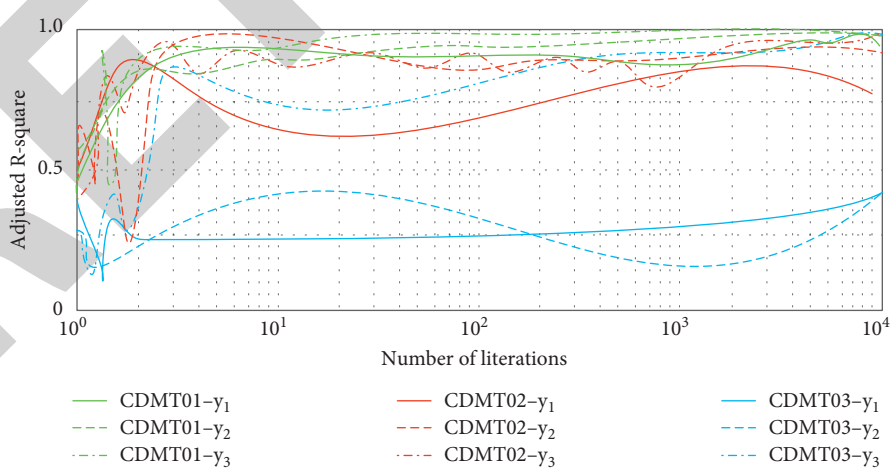

Figure 8: Trend of the adjusted R-square for the model test set during the training of the experimental model.

function is slowly improved, but in the process of continuous training of the model, the RMSE approximated by the model to each test function is also continuously improved. The RMSE variation trend of the test data set during the training of the shallow model CSMT02 is shown in Figure 10.

In Figure 10, the shallow model has reached a relatively low RMSE, with only 200 iterations in the training of approximation of each test function. Compared with the depth model CDMT01, only 150 iterations are about 33.33% slower. In the course of subsequent training, the shallow

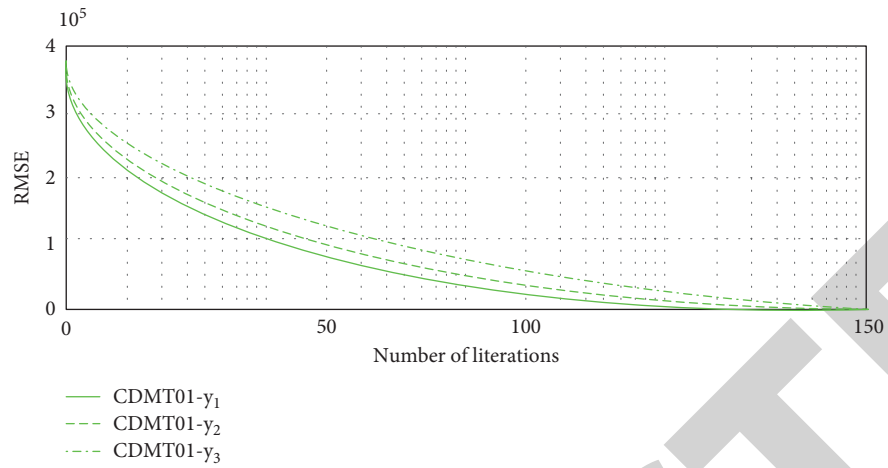

Figure 9: Trend of RMSE for the model test set during the depth model CDMT01 training.

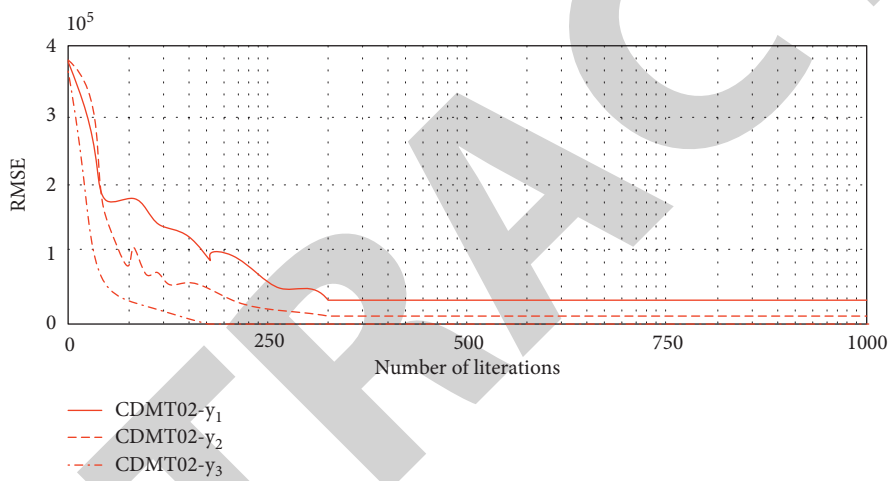

Figure 10: Trend of RMSE for the model test set during the shallow model CSMT02 training.

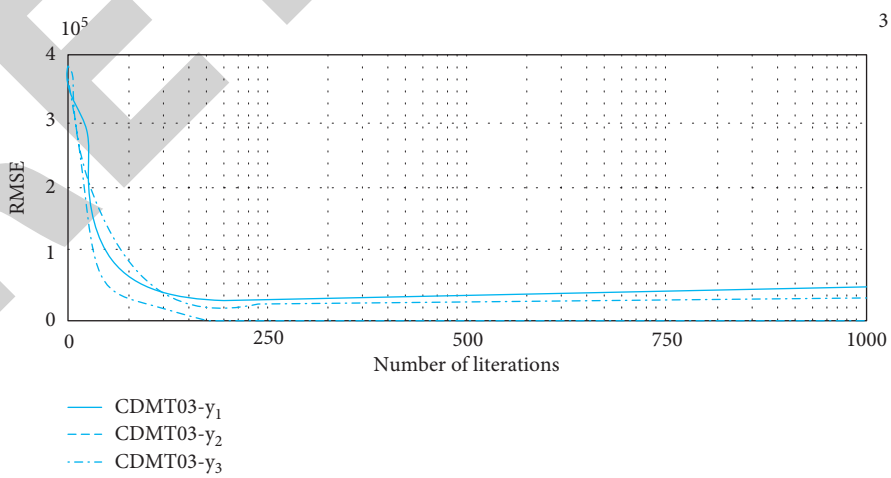

Figure 11: Trend of RMSE for the test set during the training of the shallow model CSMT03.

model is consistent with the depth model. The RMSE variation trend of the test data set during the training of the shallow model CSMT03 is shown in Figure 11.

It can be found in Figure 11 that, from the perspective of training trend, there is basically no difference between the shallow models CSMT03 and CSMT02. Although the

Table 5: Experimental model RMSE training results for the model test set.

Network model	CDMT01	CDMT02	CDMT03
Neuron number distribution	5-160-100-80-50-3	5-390-3	5-780-3
Total hidden layer neurons	390	390	780
Y_1 test data	0.15459	1.26566	0.28956
Y_2 test data	0.01484	3.16544	1.64326
Y_3 test data	0.02459	3.16478	2.16542
Number of iterations	9900	9999	9999

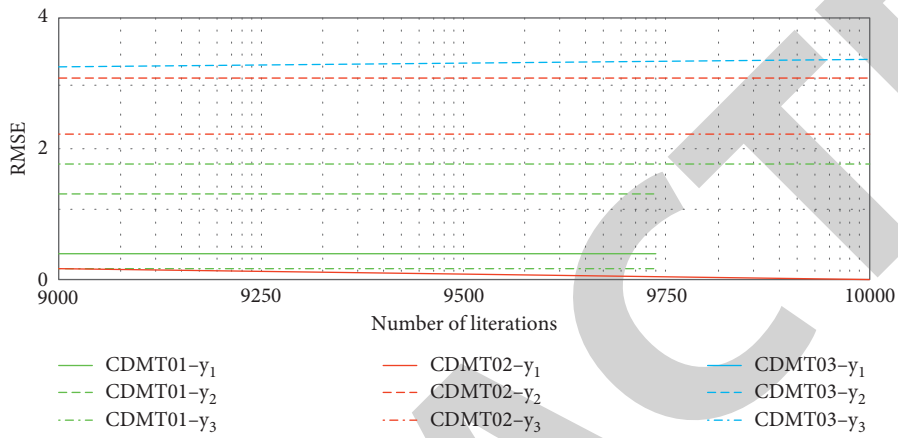

Figure 12: Partial enlargement of the trend of the RMSE for the model test set at the end of the experimental model training.

shallow model CSMT03 has more hidden layer neurons than CSMT02, the model CSMT03 is worse than CSMT02 on the whole in terms of the accuracy result of function approximation of the model.

The synchronous approximation effect of the experimental model to the three test functions is shown in Table 5 and Figure 12.

The test results show that the depth network model can effectively approximate three test functions with different data distribution and difficult function approximation at the same time compared with the traditional response surface. Compared with the shallow model as a contrast model, the adjusted R-square of fitting degree of the test function is nearly 3 times higher than that of the test function. At the same time, the RMSE of fitting accuracy index is even nearly 7 times higher for a test function.

6. Conclusion

Based on clustering and deep belief network model, the evaluation method of cultural and creative design is studied in this paper, which mainly includes cultural and creative design plan analysis and evaluation index weight calculation method, cultural and creative design plan evaluation model based on deep belief network, and cultural and creative design plan evaluation method based on clustering. Moreover, the methods and techniques proposed in this paper are applied to the evaluation of cultural and creative design schemes to simulate the cultural and creative design platform, and the theoretical methods of this paper are verified through tests.

The use of deep belief networks and convolutional neural networks has achieved excellent results in image recognition and classification. However, it is difficult to directly apply to the evaluation of cultural and creative design schemes. If the information can be extracted from the design scheme described by the two-dimensional image, and the deep learning model can be used to obtain the scoring result, the accurate expression of the data can be combined with the accurate output of the evaluation result, which is more conducive to cultural and creative design.

Data Availability

All data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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