EAI Endorsed Transactions
on Scalable Information Systems
Research Article EAI.EU

Study of Methods for Constructing Intelligent Learning Models Supported by Artificial Intelligence

Lijun Pan[1,*]

[1] College of Elementary Education Zhengzhou Normal University, Zhengzhou 450044, Henan, China

Abstract

INTRODUCTION: As the essential part of intelligent learning, innovative learning model construction is conducive to improving the quality of intelligent new teaching models, thus leading the deep integration of teaching and artificial intelligence and accelerating the change and development of teaching supported by artificial intelligence.
OBJECTIVES: Aiming at the current intelligent teaching evaluation design method, there are problems such as more objectivity, poor precision, and a single method of evaluation indexes.
METHODS: his paper proposes an intelligent learning construction method based on cluster analysis and deep learning algorithms. First of all, the intelligent learning model construction process is sorted out by clarifying the idea of clever learning model construction and extracting model elements; then, the intelligent learning model is constructed through a K-means clustering algorithm and deep compression sparse self-encoder; finally, the effectiveness and high efficiency of the proposed method is verified through simulation experiment analysis.
RESULTS: Solved the problem that the intelligent learning model construction method is not objective enough, has poor accuracy and is not efficient enough.
CONCLUSION: The results show that the proposed method improves the model's accuracy.

Keywords: Intelligent learning model, Model element extraction, K-means clustering algorithm, Deep compression sparse self-encoder

Received on 12 October 2023, accepted on 11 January 2024, published on 11 January 2024

Copyright © 2024 Pan, licensed to EAI. This open-access article is distributed under the terms of the CC BY-NC-SA 4.0, which permits copying, redistributing, remixing, transforming, and building upon the material in any medium so long as the original work is properly cited.

doi: 10.4108/eetsis.4622

*Corresponding Author. Email: lijunpan@zznu.edu.cn

1. Introduction

With the rapid development of computer technology and artificial intelligence algorithms, a new model of talent cultivation based on the Internet and artificial intelligence technology is gradually formed [1]. As a vital part of the construction of the new talent cultivation model, innovative learning has received the attention and investment of education experts. Moreover, an innovative learning model is the critical core technology of intelligent learning, and constructing an innovative learning model has become an important task and challenge in innovative learning [2]. Currently, the application of information technology in the field of education only as an auxiliary tool, only in the original teaching mode, improves teaching efficiency but does not manage to do the deep integration of information technology and education, did not significantly change to improve the quality of classroom teaching [3]. As the essential part of intelligent learning, constructing an intelligent learning model is conducive to improving the quality of intelligent new teaching modes, thus leading to the deep integration of teaching and artificial intelligence and accelerating the change and development of teaching under the support of artificial intelligence. Therefore, it is essential to study how to use artificial intelligence technology to build an efficient, accurate and personalized innovative learning model [4].
As a powerful support for the construction of high-quality education, personalized training, and scaled education,

innovative learning should study the smart learning model based on learning data and the intelligent learning model that can reflect the learning knowledge and cognitive structure [5]. Domestic and foreign scholars still need to form a unified and standardized research vein on intelligent learning, which is usually understood and analyzed from three perspectives: technology, learners, and technology learners. From the technology perspective, innovative learning is mainly used for the intelligence of the learning environment. Literature [6] defines the concept of intelligent learning as the use of the Internet and other technologies to enhance the learning ability; literature [7] through the design of self-learning environments, the use of good artificial intelligence technology, assisting the learners to access learning resources, and strengthen the interaction with the students and teachers; literature [8] according to the needs of the learner, the Smart Learning model adaptively provides learning resources for learners and constructs learning models used to carry out learning activities; Literature [9] defines that Smart Learning model can utilize all kinds of data for learning and carry out multi-perspective reasoning and analysis using artificial intelligence technology. From the learner's perspective, intelligent learning is a result, mainly used to cultivate various types of talents; literature [10] defines the intelligent learning model through intelligent devices, using machine learning technology to predict and analyze the learner's learning data; literature [11] uses data mining technology, reasoning and analysis algorithms to train the subject's learning style, and uses a variety of augmentation techniques to improve the learner's ability; literature [12] takes the learner-centred, intelligent learning to support learners in any place, any time, recognize the content to build a new model of intelligent learning based on the network and intelligence; literature [13] believes that intelligent learning is the intelligent learning style, building a variety of intelligent algorithms for learning, to improve the efficiency of learning and enhance the quality of teaching. From the technology-learner perspective, intelligent learning combines technology and learners, using intelligent technology, carrying out intelligent learning activities, allowing the learning subject to participate in the learning process actively, and cultivating intelligent talents; literature [14] constructs an intelligent learning model from the multi-dimensional aspects of teaching methods, learning psychology, learning attitudes, etc., to promote learners' learning motivation and enthusiasm, and improve learners' learning ability; literature [15] puts forward the intelligent learning environment based on network mobile terminals, which can not only develop learners' learning space, but also improve learners' ability to cultivate learning; literature [16] believes that intelligent learning activities can be carried out to make learners actively participate in the learning process, and cultivate intelligent talents.

Cluster analysis [19] is an unsupervised learning machine learning method that divides the objects in a dataset into different groups or "clusters" so that objects within the same group have a higher degree of similarity. In comparison, objects between different groups have a lower degree of similarity. Cluster analysis has many applications, such as market segmentation, image segmentation, text categorization, etc. [20]. Deep learning is a machine learning approach that mimics the human brain's neural network, modelling and abstracting data through multilevel nonlinear transformations. The advantage of deep learning is that it learns features automatically, without human intervention, and therefore can handle very complex data such as images, speech, and natural language. Deep learning has succeeded in computer vision, speech recognition, and natural language processing [21]. Applying cluster analysis algorithms and deep learning algorithms in constructing intelligent learning models makes intelligent learning models more efficient and becomes a hotspot for experts' research.

Aiming at the problems existing in the current intelligent learning construction method, this paper proposes an intelligent learning construction method based on a clustering analysis algorithm and deep learning algorithm. The main contributions of this paper are: (1) clarifying the idea of an intelligent learning model, analyzing the principle of model construction, and extracting the elements of the learning model; (2) describing the process of intelligent learning model construction; (3) combining the clustering technology and deep learning technology to construct an intelligent learning model; and (4) verifying the validity and high efficiency of this paper's method through simulation.

2. Intelligent learning model construction ideas

To better construct the intelligent learning model and understand the learning model process, this section extracts the learning model elements by clarifying the intelligent learning model ideas based on the principled model construction.

2.1 Intelligent Learning Model Construction Ideas

According to the "model construction method" [22], institutions and expert opinion, the basic process of intelligent learning model construction should include intelligent learning model elements extraction, model structure establishment and model characterization, as shown in Figure 1, the specific description is as follows:

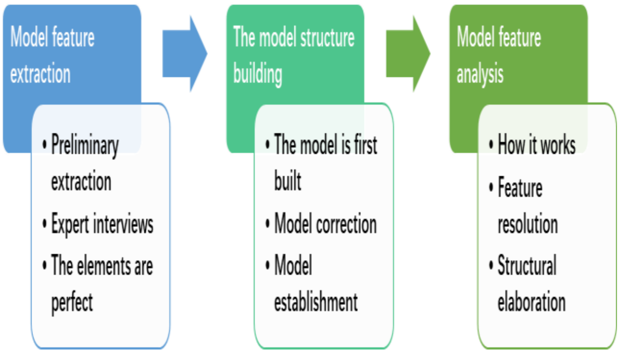

Figure 1 Schematic diagram of the idea of intelligent learning model construction

(1) Extraction of Intelligent Learning Model Elements

Wisdom learning model elements extraction is generally done through literature analysis and expert analysis, combined with the characteristics of wisdom learning model structure, using the Delphi method, to propose the model elements of wisdom learning.

(2) Intelligent learning model structure establishment

Wisdom learning model construction is based on extracting constituent elements, exploring the inner relationship of the learning wisdom model, initially establishing the wisdom learning model, and correcting the model by utilizing expert appraisal and multiple rounds of iterative cycle learning.

(3) Characterization of intelligent learning model

After the model is constructed, the intelligent learning model characterization utilizes machine learning algorithms to analyze the intelligent learning features from the model operation mechanism, element resolution, structure elaboration and other aspects.

2.2 Principle of Intelligent Learning Model Construction

The construction of the intelligent learning model requires characterizing the constituent elements and the intrinsic mapping relationship. To objectively, comprehensively and scientifically express the portrayal of the intelligent learning model, this section proposes the principles of intelligent learning model construction, including intelligent support, theoretical guidance, informatization needs, and disciplinary competence cultivation, as shown in Figure 2.

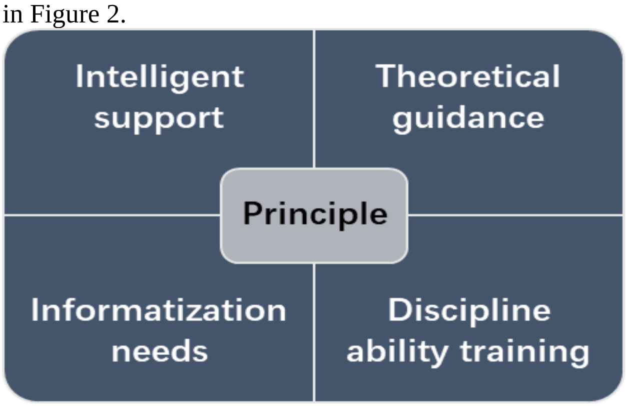

Figure 2 Principles of intelligent learning model construction

(1) Intelligent Support

The intelligent learning model based on AI technology is mainly centred on the method of AI technology, which requires support for establishing the structure of the intelligent learning model and the construction method of the intelligent learning model.

(2) Theoretical guidance

In the process of constructing the intelligent learning model, the intelligent learning model with the integration of science and technology is formed by analyzing the law of learning and taking the constructivist learning theory, the multiple intelligence theory, and the connected attention learning theory as the guiding principles.

(3) Informatization Needs

Based on the current development needs of education informatization and intelligence, the intelligent learning model uses artificial intelligence technology to build an accurate learning model for talent cultivation, which makes the whole process of the intelligent learning model information.

(4) Discipline Competency Cultivation

Cultivation of subject competence indicates that the intelligent learning model is constructed with the cultivation of crucial subject competence as the ultimate goal, centring on the fundamental goal of establishing morality, educating people, and improving the learning ability of learners through intelligent subject courses.

2.3 Extraction of elements of intelligent learning model construction

The elements are analyzed and selected according to the principled nature of clever learning model construction by analyzing the idea of the intelligent learning model. Collecting learning data, this section initially selects the elements of the whole process of intelligent learning, including learner elements, learning content, learning resources, learning data, learning activities, and learning evaluation, which are described as follows:

(1) Learner

The learner element refers to the main body that obtains knowledge resources and analysis results through learning and other methods as well as the group learning collective, and the specific elements include individual learners and group learners.

(2) Learning content

Learning content refers to the goal learners have to achieve through learning, including basic knowledge, fundamental skills, learning methods, and value orientation; specific elements include knowledge, method, and emotional goals.

(3) Learning resources

The element of learning resources refers to the learning materials to be utilized by the learners in the learning process, the support tools for researching problems and the support environment for carrying out interactive activities. Moreover, the specific elements include digital materials, learning tools, and learning systems.

(4) Learning data

The elements of learning data refer to the data of students' classroom practice, after-class homework data, and stage examination results data, and the specific elements include practice data, homework data, and examination data.

(5) Learning activities

The elements of learning activities refer to the learning problems encountered in the learning process, tasks, learning-specific operations, learning regulation and optimization; the specific elements include learning problems, learning process, and learning testing.

(6) Learning Evaluation

Learning evaluation elements refer to the evaluation of the learning subject before learning, during the learning process, and after the end of learning activities, and the specific elements include diagnostic evaluation, formative evaluation, and summative evaluation.

2.4 Smart Learning Model Structure System

The structure system of innovative learning model takes the elements of learner, learning content, learning resources, learning data, learning activities, learning evaluation [23] as the first-level elements, and individual learners, group learners, knowledge goals, method goals, emotional goals, digital materials, learning tools, learning systems, practice data, homework data, test data, learning problems, learning process, learning testing, diagnostic evaluation, formative evaluation, summative evaluation, and final evaluation as the first-level elements. Evaluation, formative evaluation, summative evaluation and other 17 specific elements for the second level elements [24] fully embody the whole process of the intelligent learning model to build a scientific, objective and comprehensive innovative learning model structure system. The specific schematic diagram is shown in Figure 3.

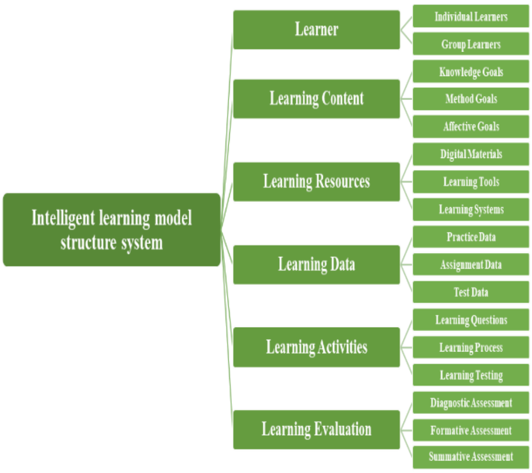

Figure 3 The structure system of the full-process innovative learning model

3. Smart learning model construction

According to the idea of intelligent learning model construction in the previous section, this section utilizes the core elements. It divides the innovative learning model construction process into four key steps: learning environment construction, learning path clustering, learning data training, and learning effect evaluation. Learning environment construction, as the grassroots building of clever learning model construction, requires designing hardware environment, software environment, and environment intelligence, i.e., environment configuration and flush. Learning path clustering analysis mainly uses learning activities, learning mode, and learning state data to characterize the features, using clustering unsupervised analysis algorithms to categorize the data and then using expert experience or template comparison to crown the label. Learning data training uses the clustered dataset, input learning features, analysis of learning behaviours, and deep learning algorithms to train the data and construct intelligent learning models. Learning effect evaluation mainly refers to evaluating and analyzing the learning path clustering analysis and learning model construction results. The schematic diagram of the intelligent learning model construction process is shown in Figure 4.

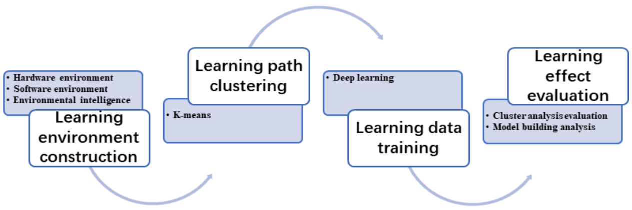

Figure 4 Schematic diagram of the intelligent learning model construction process

4. K-means clustering algorithm

The role of the clustering algorithm is to classify a large number of complex learning activities, learning styles, and learning status data into one category according to the learning attributes of similar data, laying the foundation for the next step of the intelligent learning model training. Accurately categorizing data directly affects the construction of the sample set, so it is crucial to find a high-performance clustering algorithm.

The K-means algorithm is currently the most popular divisive clustering algorithm, which performs well in big data classification [25]. The algorithm determines the clustering centers and the elements to which they belong by minimizing an objective function based on the squared error. The aim is to keep the cluster centers as far away from each other as possible and associate each data point to the nearest cluster center [13]. The Euclidean distance is commonly used as a similarity measure in the K-means algorithm, where a small distance indicates substantial similarity while a considerable distance indicates low similarity.

The objective function of the K-means algorithm is defined as follows:

$$J=\sum_{i=1}^{K}\left(\sum_{k}\left\|x_k-c_i\right\|^2\right) \tag{1}$$

In the formula, K is the number of clusters, c_i is the center of the cluster, and x_k is the k-th data point in the i-th cluster.

The specific procedure of the algorithm is as follows:

Step 1: Determine the total number of classification classes K and randomly select K cluster class centers $C=(c_1,c_1,\cdots,c_K)$.

Step 2: Calculate the partition matrix. The data point belongs to the cluster with the closest center to the data point. Therefore, the cluster is represented by a binary partition matrix U. The elements in U are determined as follows:

$$u_{ij}=\begin{cases}1 & if\ \left\|x_j-c_i\right\|^2\le\left\|x_j-c_t\right\|^2, \forall t\neq i\\ 0 & otherwise\end{cases} \tag{2}$$

In the formula, u_{ij} represents whether the j-th data point belongs to the i-th cluster class.

Step 3: Update the cluster center. The center c_i of each cluster class that minimizes the objective function is defined as follows:

$$c_i=\frac{\sum_{j=1}^{N}u_{ij}x_j}{\sum_{j=1}^{N}u_{ij}} \tag{3}$$

In the equation, N represents the number of samples.

Step 4: Compute the objective function using equation (1). Verify that the function converges, or the difference between two neighbouring values of the objective function is less than a given threshold and stops. Otherwise, repeat step 2.

5. Deep Compression Sparse Self-Encoder

5.1 Sparse Self-Encoding Network

A self-encoder is a feed-forward neural network reconstructing the input data [26]. This network can use unsupervised learning to extract low-dimensional feature vectors from the original input vectors for data dimensionality reduction. The standard self-encoder is a three-layer network with input, hidden, and output layers, and its structure is symmetric. It can be divided into two parts: encoder and and decoder. Figure 5 shows the basic structure of the self-coding network, where the role of the encoding network is to allow the input vector to be mapped to the hidden layer, thus achieving dimensionality reduction. The decoding network maps the feature extraction from the hidden layer to the input to complete the reconstruction of the input information. This stage can be regarded as the inverse process of the encoding stage. Suppose the reconstructed data is equal to the original input data given the visible layer. In that case, the activation patterns in the hidden layer can be regarded as a compressed representation of the input data. Overall, the operational process of the self-coding network is divided into two steps: In the first step, the input data of the given visible layer is encoded, and the activation patterns in the hidden layer are generated. In the second step, the activation patterns in the hidden layer are decoded, and the output data of the reconstructed layer is generated.

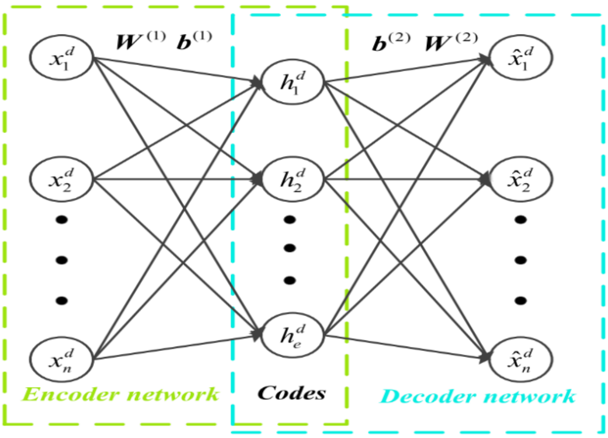

Figure 5 Basic structure of the self-coding network

The goal of the self-encoder is to accomplish the following form of learning:

$$\hat{\boldsymbol{x}}=f_{\boldsymbol{W},\boldsymbol{b}}(\boldsymbol{x})\approx\boldsymbol{x} \tag{4}$$

In the equation, $\boldsymbol{x}$ inputs the vector, while $\boldsymbol{W}=(W_1,W_2)$ and $\boldsymbol{b}=(b_1,b_2)$ represent the weights and deviations of the two layers, respectively. Given the input vector $\boldsymbol{x} \in [0,1]^n$, during the encoding phase, it is first mapped to the hidden layer representation through a deterministic mapping parameterized by $\theta_1 = (W_1, b_1)$, which can represent:

$$h = g_{\theta_1}(\boldsymbol{x}) = \sigma(W_1 \boldsymbol{x} + b_1) \tag{5}$$

In the equation, , $\boldsymbol{h} \in [0,1]^{n'}$, $\boldsymbol{W}_1 \in R^{n' \times n}$, $\boldsymbol{b}_1 \in R^{n' \times 1}$, and $\sigma(x) = 1/(1+\exp(-x))$ are sigmoid activation functions. Then, during the decoding process, the hidden layer representation $\theta_2 = (W_2, b_2)$ is mapped back to the reconstruction vector $\boldsymbol{h}$ using the parameterized mapping function $\hat{\boldsymbol{x}} \in [0,1]^n$, which is represented as:

$$\hat{\boldsymbol{x}} = g_{\theta_2}(\boldsymbol{h}) = \sigma(W_2 \boldsymbol{h} + b_2) \tag{6}$$

In the equation, $\boldsymbol{W}_2 \in R^{n' \times n}$, $\boldsymbol{b}_1 \in R^{n' \times 1}$. In order to optimize the model parameters in (1), i.e. $\theta = (\theta_1, \theta_2)$, the average reconstruction error is used as the cost function:

$$J_{AE}(\boldsymbol{W}, \boldsymbol{b}) = \frac{1}{m} \sum_{r=1}^{m} \frac{1}{2} \left\| \hat{\boldsymbol{x}}^{(r)} - \boldsymbol{x}^{(r)} \right\|^2 \tag{7}$$

In the formula, m is the overall number of training samples. Usually, a weight attenuation term needs to be added to the above equation to prevent overfitting, namely:

$$J_{AE}(\boldsymbol{W}, \boldsymbol{b}) = \frac{1}{m} \sum_{r=1}^{m} \frac{1}{2} \left\| \hat{\boldsymbol{x}}^{(r)} - \boldsymbol{x}^{(r)} \right\|^2 + \frac{\lambda}{2} \sum_{l=1}^{2} \sum_{i=1}^{s_l} \sum_{j=1}^{s_{l+1}} (w_{ij}^{(l)})^2 \tag{8}$$

W In the formula, λ is the weight attenuation coefficient of the autoencoder, s_l is the number of all neurons in layer l , and $w_{ij}^{(l)}$ is the weight values of neurons l connected in layer i and $l+1$ connected in layer j .

Adding sparse constraints to the hidden layer is a more effective approach to extract clearer feature information while avoiding simple replication of the input layer by the reconstruction layer. The KL (Kullback Leibler, KL) divergence function can reflect the differences between different distributions, and using this function to construct sparse penalty terms can achieve the goal of limiting the activation of hidden unit h . Assuming $h_j(\boldsymbol{x}^{(r)})$ represents the activation value of hidden layer neuron j relative to input $\boldsymbol{x}^{(r)}$, the average activation value of hidden units is defined as follows:

$$\hat{\rho}_j = \frac{1}{m} \sum_{r=1}^{m} h_j(\boldsymbol{x}^{(r)}) \tag{9}$$

To enhance the sparsity of the hidden layer, select a sparsity parameter ρ with a value size close to 0 and set $\hat{\rho}_j = \rho$. Attempt to minimize the KL divergence between $\hat{\rho}_j$ and ρ as follows:

$$J_{KL}(\rho \| \hat{\rho}_j) = \sum_{j=1}^{n'} \rho \log \frac{\rho}{\hat{\rho}_j} + (1-\rho) \log \frac{1-\rho}{1-\hat{\rho}_j} \tag{10}$$

From the above equation, it can be seen that when the values of $\hat{\rho}_j$ and ρ are closer, the value of KL is smaller, and vice versa, the value of KL is larger. Therefore, when ρ approaches zero, the KL divergence is minimized, and $\hat{\rho}_j$ also approaches zero, deactivating hidden layer neurons, thereby enhancing the sparsity of feature representation. In this article, ρ is set to 0.05. According to Equation (9), the sparse constraint term is:

$$J_{Sprase}(\boldsymbol{W}, \boldsymbol{b}) = \beta J_{KL}(\rho \| \hat{\rho}_j) \tag{11}$$

where $\beta \in [0,1]$ is the sparse penalty term weight? Substituting Equation (10) into Equation (7), the complete cost function of the Sparse Auto Encoder (SAE) network is obtained as:

$$\begin{aligned} J_{SAE}(\boldsymbol{W}, \boldsymbol{b}) &= J_{AE}(\boldsymbol{W}, \boldsymbol{b}) + J_{Sparse}(\boldsymbol{W}, \boldsymbol{b}) \\ &= \frac{1}{m} \sum_{r=1}^{m} \frac{1}{2} \left\| \hat{\boldsymbol{x}}^{(r)} - \boldsymbol{x}^{(r)} \right\|^2 + \frac{\lambda}{2} \sum_{l=1}^{2} \sum_{i=1}^{s_l} \sum_{j=1}^{s_{l+1}} (w_{ij}^{(l)})^2 + \beta J_{KL}(\rho \| \hat{\rho}_j) \end{aligned} \tag{12}$$

5.2 Compressed Sparse Auto Encoder Network

SAE can better solve the problem of information redundancy, but the network itself is weak against interference, less robust, and less capable of generalization. To improve the robustness of the SAE network and the classification accuracy, the compressed self-coding network is integrated into the sparse self-coding network, and the compressed sparse self-coding network is proposed.

Compressed Auto Encoder (CAE) is a feature learning algorithm that can obtain local manifold structures and has the potential for non local generalization [27]. CAE utilizes the Frobenius norm of the Jacobian matrix of the input data as a penalty term and adds it to the loss function of the standard autoencoder, compressing the mapping of the feature space within the domain of the training data, thereby enhancing the robustness of the network. For input data x^r , the feature representation h^r of the hidden layer, and its Jacobian matrix $J_f(x^r)$, can be represented as:

$$J_f(x^r) = \frac{\partial h^r}{\partial x^r} = \begin{bmatrix} \frac{\partial h_1^r}{\partial x_1^r} & \cdots & \frac{\partial h_1^r}{\partial x_n^r} \\ \vdots & \ddots & \vdots \\ \frac{\partial h_{n'}^r}{\partial x_1^r} & \cdots & \frac{\partial h_{n'}^r}{\partial x_n^r} \end{bmatrix} \tag{13}$$

CAE can effectively eliminate the inter-class error of high-dimensional data, improve the generalization ability of network feature extraction, and maximize the distinction between different features. The loss function of CAE is defined as follows:

$$\begin{aligned} J_{CAE}(W,b) &= J_{AE}(W,b) + J_{Contractive}(W,b) \\ &= \frac{1}{m}\sum_{r=1}^{m}\left(\frac{1}{2}\left\|\hat{x}^{(r)} - x^{(r)}\right\|^2 + \frac{\zeta}{2}\left\|J_f(x^r)\right\|_F^2\right) + \frac{\lambda}{2}\sum_{l=1}^{2}\sum_{i=1}^{s_l}\sum_{j=1}^{s_{l+1}}(w_{ij}^{(l)})^2 \end{aligned} \tag{14}$$

Where ζ denotes the compression coefficient.
In summary, the loss function of CompressiveSparse Auto Encoder (CSAE) is defined as follows:

$$\begin{aligned} J_{CSAE}(W,b) &= J_{CAE}(W,b) + J_{Sprase}(W,b) \\ &= \frac{1}{m}\sum_{r=1}^{m}\left(\frac{1}{2}\left\|\hat{x}^{(r)} - x^{(r)}\right\|^2 + \frac{\zeta}{2}\left\|J_f(x^r)\right\|_F^2\right) + \beta J_{KL}(\rho\|\hat{\rho}_j) + \frac{\lambda}{2}\sum_{l=1}^{2}\sum_{i=1}^{s_l}\sum_{j=1}^{s_{l+1}}(w_{ij}^{(l)})^2 \end{aligned} \tag{15}$$

5.3 DCSAE Classification Network

The classifier is a necessary component for constructing a deep classification network. Since air combat posture assessment is a multi-classification problem, the Softmax classifier is chosen to classify the air combat posture. As a supervised regression model, Softmax is a form of generalization of the binary logistic regression classifier to multiple classes. It can have a corresponding probabilistic interpretation for each category when the class labels are multiple [28].
As a shallow network, the CSAE with a single hidden layer has limited feature extraction ability for input data, especially when facing high-dimensional nonlinear data; it cannot effectively extract the critical information of the data, which in turn affects the accuracy of the classifier. The deep neural network is a multi-hidden layer machine learning model with a more robust feature abstraction capability, which can remove redundant information and better characterize the original data. Therefore, deep CSAE is considered, and a Deep ContractiveSparse Auto Encoder (DCSAE) classification network is proposed.DCSAE comprises multiple CSAE stacks, which belong to typical semi-supervised learning. The whole training process can be divided into unsupervised pre-training (Pre-training) and supervised fine-tuning (Fine-training). The essence of pre-training is to obtain the network's initial weights and bias values through the gradient descent algorithm. This process will be trained layer by layer using a greedy strategy. The first autoencoder's output will be the second autoencoder's input. In contrast, the output of the second autoencoder will be the input of the third autoencoder, and so on. To finalize the training the training process is shown in Figure 6.

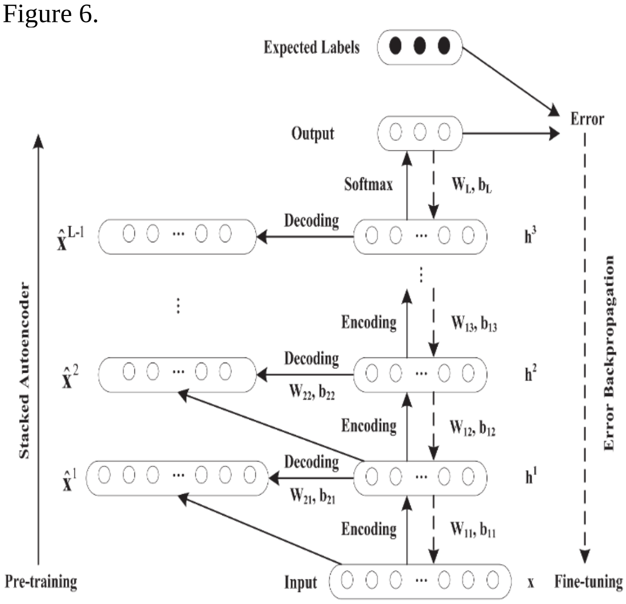

Figure 6 Basic structure of the DCSAE network

6. Smart learning model construction process based on intelligent clustering analysis algorithm and deep learning methods

The intelligent learning model based on intelligent clustering analysis algorithm and deep learning method is divided into learning environment construction module, data preprocessing module, clustering analysis module, model construction module, and model evaluation module, as shown in Figure 7. Firstly, the data are input and preprocessed; then, the learning activity, learning mode, and learning state data are clustered and analyzed by using the K-means clustering algorithm; secondly, the clustered data are labelled, and the DCSAE classification network is used for training; finally, the clustered data and the model evaluation data are analyzed for the learning effect.

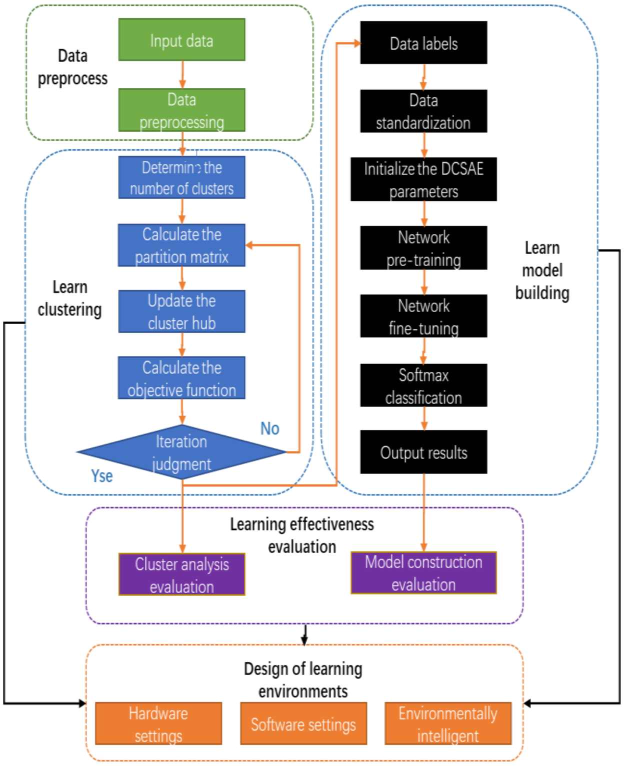

Figure 7 Flow chart of intelligent learning model construction

6.1 Algorithm and environment parameter setting

To verify the accuracy and timeliness of the intelligent learning model proposed in this paper, five smart learning model algorithms are selected for comparison, and the specific parameter settings of each algorithm are shown in Table 1 and Table 2. The data for clever learning model construction are mainly from the case school's learning situation, including the learning activities, learning styles, and learning status data.

Table 1 Parameter settings of clustering analysis method for innovative learning model

Algorithm	Parameter Settings
SOM	The dimension of the input is 8, and the number of neurons in the output layer is 4
FCM	The index of the affiliation matrix is 2, the maximum number of iterations is 100, and the iteration termination condition is a minimum change in affiliation of 1.0e-5;
HC	Spearman correlation coefficient distance measure, the number of clusters was calculated using a weighted average (weighted) method;
DBSCAN	Neighbourhood distance threshold ϵ versus the number of samples MinPts is obtained by fitting a polynomial to the curve;
DPC	Parameter-free
K-means	Euclidean distance is used, and the number of clusters is set to 4

Table 2 Parameter settings for the intelligent learning model building approach

Algorithm	Parameter setting
RF	N_tree= 500.m_try=$floor$($8^{0.5}$)
RBF	The number of hidden layer nodes is 10
MSVR	The MSVR portion$C$= 1000, andε= 0.01, using a radial basis kernel function ofσ= 0.5;
SAE-MSVR	The SAE part includes two self-encoders with the number of nodes in each hidden layer being 10, 8; The MSVR part$C$=1000.ε= 0.01, using a radial basis kernel function ofσ= 0.5;
CNN	Convolutional layer (30 convolutional kernels, Relu activation), Maximized pooling layer, Fully connected layer (60 nodes, Relu activation), softmax layer, Output layer; Weight initialization is initialized with Gaussian distribution, Training algorithm is Adam's algorithm; Learning rate is 0.001, L2 regularization coefficient is 0.004, MaxEpochs is 100, Minimum batch processing The number of samples MiniBatchSize is 20;
DCSAE	number of nodes in the first hidden layer is 20, the number of nodes in the second hidden layer is 25, the number of nodes in the third hidden layer is 15, learning efficiency is 0.0238, sparsity coefficients are 0.3245, 0.2109, and 0.0027, and sparsity weight is 0.0046

6.2 Cluster Analysis

To analyze the clustering analysis results of learning activities, learning styles, and learning status data, this section uses clustering evaluation indexes to evaluate the clustering. In the unavailability of learning data clustering classification criteria, intrinsic assessment methods based on the tightness of data points within clusters and the separation of data points between clusters are utilized to judge the goodness of clustering. Therefore, this section adopts three intrinsic evaluation methods, including the Silhouette (Sil) evaluation index, Davies Bouldin (DB) evaluation index, and Calinski Harabaz (CH) evaluation index. The Sil evaluation index, also known as the contour coefficient, is closer to 1, indicating a more reasonable clustering; The closer it is to -1, the more it indicates that the current sample should be classified into other categories; Approximately 0 indicates that the sample should be on the boundary. The DB index mainly refers to the ratio of the distance from intra cluster samples to cluster centers to the distance between cluster centers. The smaller the value, the better the clustering results. The CH index is defined as the ratio of separation to compactness, and the higher its value, the better the clustering effect. Figures 8, 9 and 10 show the learning data clustering evaluation results. From Figure 8, it can be seen that K-means obtains the best Sil index; from Figure 9, it can be seen that K-means obtains the best DB index; and from Figure 10, it can be seen that K-means obtains the best CH index. In summary, the K-means algorithm has the best clustering effect, and the K-means algorithm is selected as the learning path clustering analysis method.

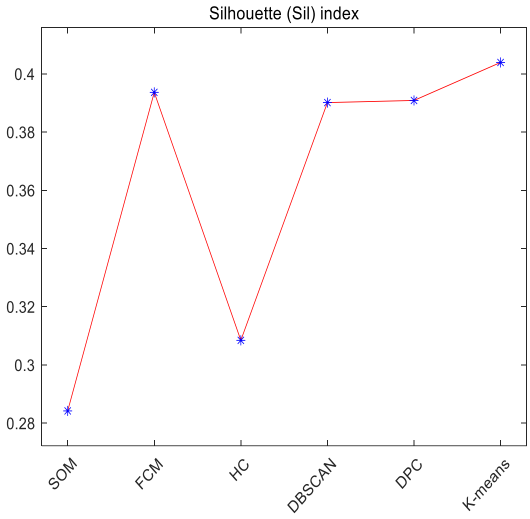

Figure 8 Sil results of different clustering algorithms

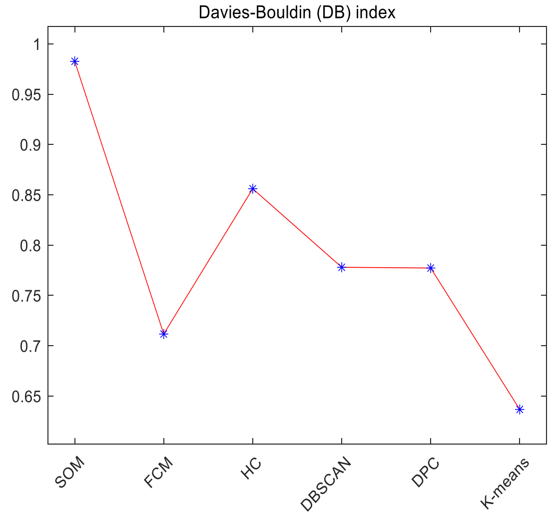

Figure 9 Different clustering algorithm DB results

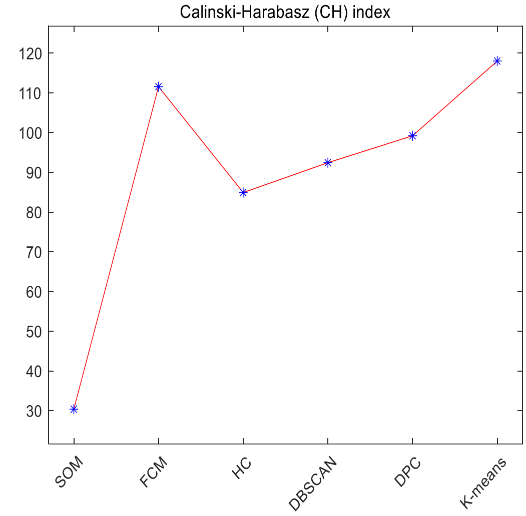

Figure 10 Different clustering algorithm CH results

6.3 Model Construction Analysis

To verify the effectiveness and robustness of the intelligent learning model construction method proposed in this paper, DCSAE is compared with five other models such as RF, RBF, MSVR, SAE-MSVR, CNN, etc., and the evaluation results of each model are shown in Figs. 11, 12, 13, 14, 15 and 16. By comparing the evaluation results in Figs. 11-16, the evaluation results of DCSAE are closer to the actual values, thus indicating that the performance of DCSAE intelligent learning model evaluation is better than RF, RBF, MSVR, SAE-MSVR, and CNN algorithms.

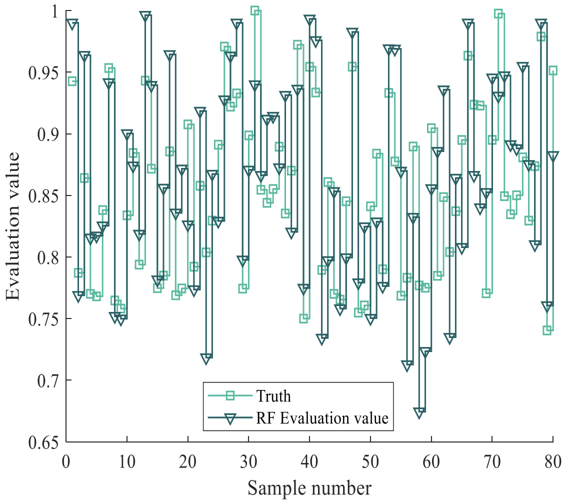

Figure 11 Evaluation results of intelligent learning model based on RF algorithm

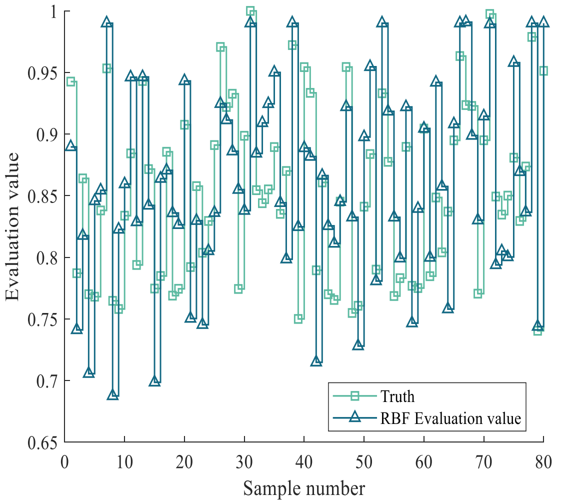

Figure 12 Evaluation results of intelligent learning model based on RBF algorithm

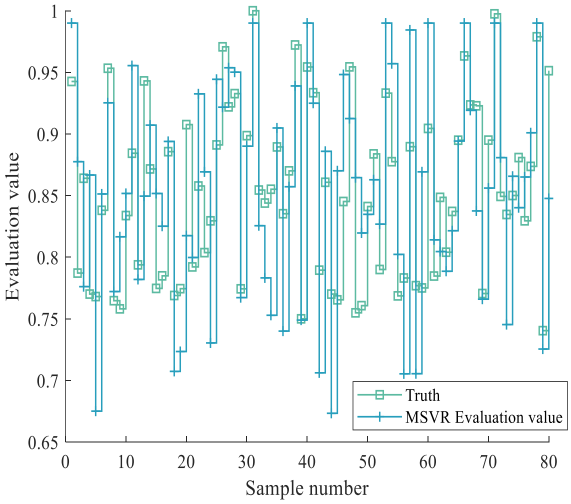

Figure 13 Evaluation results of the intelligent learning model based on the MSVR algorithm

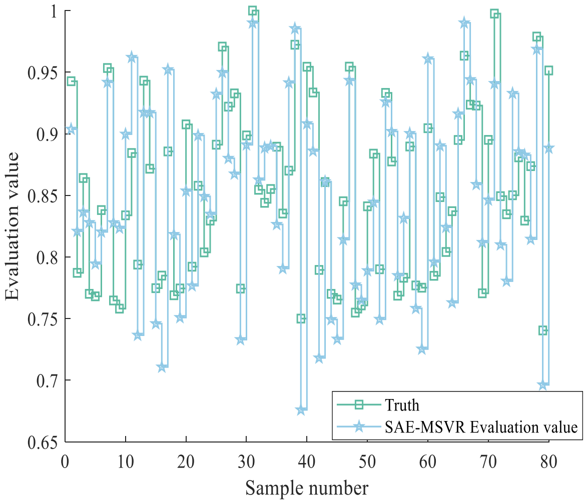

Figure 14 Evaluation results of the intelligent learning model based on the SAE-MSVR algorithm

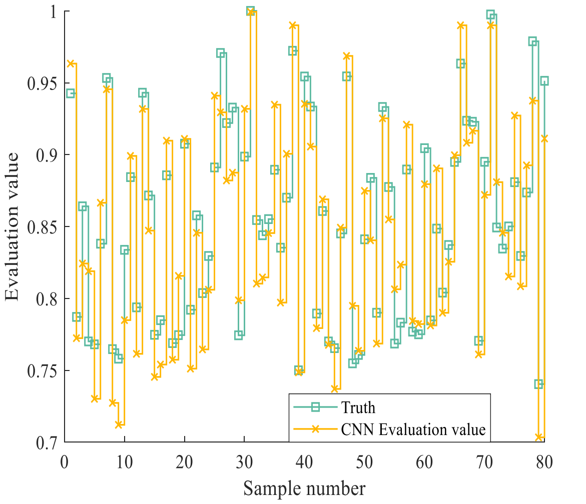

Figure 15 Evaluation results of the intelligent learning model based on the CNN algorithm

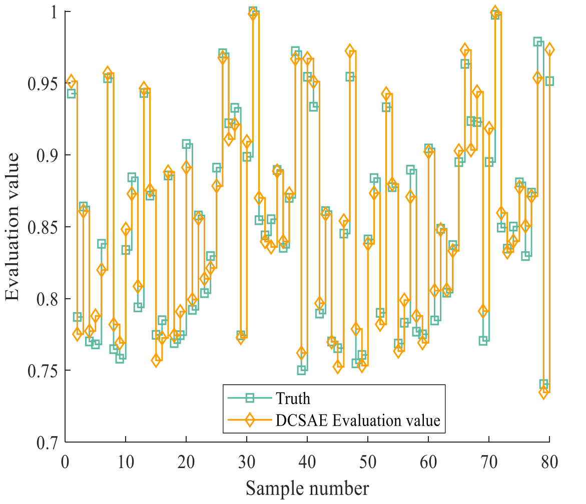

Figure 16 Evaluation results of the intelligent learning model based on the DCSAE algorithm

7 Conclusion

In order to construct a smart learning model in real-time and accurately from learning data, this paper adopts clustering algorithm and deep learning algorithm to construct a smart learning model. This method clarifies the ideas of smart learning models, extracts learning model elements based on the principles of model construction, and concretizes the process of building smart learning models. Build an intelligent learning model by combining K-means clustering algorithm with deep compressed sparse autoencoder network. The effectiveness of the proposed method was analyzed using learning activities, learning methods, and learning status data. The results showed that the proposed method outperformed other model construction algorithms in terms of clustering analysis accuracy and model evaluation. In subsequent research, the intelligent learning model will be embedded into the intelligent learning model system to further enhance the autonomy and intelligence of the intelligent learning model.

References

[1] Liu W, T, Liu Z, et al.A novel deep learning ensemble model based on two-stage feature selection and intelligent optimization for water quality prediction[J].Environmental Research. Section A, 2023.

[2] Tian T, Tongjia G, Jun C, et al.Graphic Intelligent Diagnosis of Hypoxic-Ischemic Encephalopathy Using MRI-Based Deep Learning Model[J].Neonatology, 2023.

[3] Sofy M A, Khafagy M H, Badry R M . An Intelligent Arabic Model for Recruitment Fraud Detection Using Machine Learning[J].Journal of Advances in Information Technology, 2023.

[4] Ma D, Li X, Lin B, et al.A dynamic, intelligent building retrofit decision-making model in response to climate change[J].Energy and buildings, 2023.

[5] Khan S U, Khan N, Ullah F U M, et al.Towards intelligent building energy management: AI-based framework for power consumption and generation forecasting[J].Energy and buildings, 2023.

[6] Han C, Ma T, Chen S . Asphalt pavement maintenance plans intelligent decision model based on reinforcement learning algorithm[J].Construction and Building Materials, 2021, 299(13):124278.

[7] Zhang J . Potential energy saving estimation for retrofit building with ASHRAE-Great Energy Predictor III using machine learning[J].Proceedings of the 2021 1st International Conference on Control and Intelligent Robotics, 2021

[8] Wang C , Yu Q , Law K H ,et al.Machine Learning-based Regional Scale Intelligent Modeling of Building Information for Natural Hazard Risk Management[J].BM: Bau- und mobelschreiner, 2021.

[9] Rababaah A R, Rababah A M . Intelligent machine vision model for building architectural style classification based on deep learning[J].International Journal of Computer Applications in Technology, 2022.

[10] Goliath L, Yaseen Z M . Development of a hybrid computational intelligent model for daily global solar radiation prediction[J].Expert Systems with Application, 2023.

[11] Constantin A . Intelligent Explorations of the String Theory Landscape[J].arXiv e-prints, 2022.

[12] Li K, Zhang J, Chen X, et al. Building's hourly electrical load prediction based on data clustering and ensemble learning strategy[J].Energy and Buildings, 2022, 261:111943.

[13] Al-Mhiqani M N, Ahmad R, Abidin Z Z, et al.A new intelligent multilayer framework for insider threat detection[J].Computers & Electrical Engineering, 2022, 97:107597.

[14] Xiao Y, Zhang X, Xu X, et al.Deep Neural Networks With Koopman Operators for Modeling and Control of Autonomous Vehicles[J].IEEE transactions on intelligent vehicles, 2023.

[15] Ang G M, Lim E P . Learning Semantically Rich Network-based Multi-modal Mobile User Interface Embeddings[J].ACM Transactions on Interactive Intelligent Systems, 2022, 12:1 - 29.

[16] Xie J, Xu X, Wang F, et al.Modelling adaptive preview time of driver model for intelligent vehicles based on deep learning[J].Proceedings of the Institution of Mechanical Engineers, Part I. Journal of Systems and Control Engineering, 2022(2):236.

[17] Researchers Submit Patent Application, 'Systems And Methods For Identifying Processes For Robotic Automation And Building Models Therefor,' for Approval (USPTO 20220171988)[J].Robotics & Machine Learning Daily News, 2022.

[18] Ratican J, Hutson J, Wright A.A Proposed Meta-Reality Immersive Development Pipeline: Generative AI Models and Extended Reality (XR) Content for the Metaverse[J].Journal of Intelligent Learning Systems and Applications, 2023.

[19] Guan X, Li W, Huang Q, et al.Intelligent colour matching model for wood dyeing using Genetic Algorithm and Extreme learning machine[J].Journal of Intelligent & Fuzzy Systems: Applications in Engineering and Technology, 2022.

[20] Diana E V, Sumathi M . An Intelligent Deep Learning Architecture Using Multi-scale Residual Network Model for Image Interpolation[J].Journal of Advances in Information Technology, 2023.

[21] Huang Y, Dai H, Tseng V S . Periodic Attention-based Stacked Sequence to Sequence framework for long-term travel time prediction[J].Knowl. Based Syst. 2022, 258:109976.

[22] Ayoub B, Nora T . An optimized Parkinson's disorder identification through evolutionary fast learning network[J].International Journal of Intelligent Computing and Cybernetics, 2022.

[23] Zhong Zhuo. Research on the Construction and Application of Smart Learning Model Supported by Artificial Intelligence [D]. Northeast Normal University,2023.

[24] Zhang R, Lu S, Wang X, et al.A multi-model fusion soft measurement method for cement clinker f-CaO content based on K-means ++ and EMD-MKRVM[J].Transactions of the Institute of Measurement and Control, 2023, 45(2):287-301.

[25] Burda Y, Grosse R, Salakhutdinov R . Importance Weighted Autoencoders[J].Computer Science, 2015.
[26] Burda Y , Grosse R , Salakhutdinov R .Importance Weighted Autoencoders[J].Computer Science, 2015.
[27] Zhang S , Yao L , Xu X .AutoSVD++: An Efficient Hybrid Collaborative Filtering Model via Contractive Auto-encoders[J].ACM, 2017.