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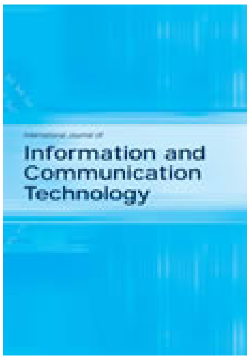

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Construction of a CS-ELM-based assessment model for civic education within a multidimensional analysis framework

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Abstract: Sophisticated technology is required to evaluate college and university ideological and political education since it shapes student values, morality, and societal obligations. This paper suggests a cuckoo search-based extreme learning machine (ELM) model optimisation approach to handle this challenge. Using CS helps to maximise ELM model input weights and biases, hence enhancing stability and assessment accuracy. The work consists in three key investigations: In evaluation accuracy, CS-ELM performs better than other optimisation techniques and the benchmark ELM model. Second, ablation studies for every model component revealed the effects on the final assessment results of the CS optimisation algorithm, input weight optimisation, bias optimisation, and other factors. At last, time consumption comparison experiments reveal that in practice the CS-ELM model has low computational demand and great assessment accuracy.

Keywords: cuckoo search; CS; extreme learning machine; ELM; ideological and political education; educational evaluation.

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1 Introduction

The evaluation of civic and political education in colleges and universities is progressively changing from the conventional human assessment mode to the direction of data-driven intelligent assessment as information technology advances constantly (Rong and Gang, 2021). The holistic evaluation of ideological and political education must take into account several elements including emotions and behavioural performance in addition to students' political and moral attitudes (Corcoran et al., 2020; Pagano and Huo, 2007). How fast and precisely to do a thorough evaluation of students' ideological and political quality in the face of massive and sophisticated multidimensional data has become a critical problem. Consequently, research hotspots based on machine learning and intelligent optimisation approaches have progressively taken front stage (Xia et al., 2022; Fan et al., 2023).

Most of the conventional approaches in the evaluation of civic education focus on subjective assessment and qualitative analysis by teachers (Yang and Chung, 2009), based on gathering knowledge in the form of questionnaires and interview records (Afolayan and Oniyinde, 2019). In small-scale individual analysis, these approaches have a certain guiding value; in large-scale student groups, objective and systematic assessment is challenging to obtain; and they frequently lack quantitative analysis of hidden elements like students' emotional and behavioural performance. Data-driven educational assessment methods have progressively being used in civic education of colleges and universities in recent years as data analysis technologies developed (Kurilovas, 2020). Text sentiment analysis techniques based on natural language processing can automatically analyse students' written comments (Naithani and Raiwani, 2023), from which their emotional attitudes towards ideological and political courses can be extracted; data mining models based on statistical methods can handle large-scale questionnaires or performance data and make predictions on students' ideological development trends by analyses of historical data (Wu et al., 2013). Most of these approaches, nonetheless, are limited to particular data dimensions, therefore neglecting the nonlinear interaction between dimensions and results in some restrictions in complicated ideological and political education assessment situations.

Globally popular intelligent optimisation methods including genetic algorithm (GA), particle swarm optimisation (PSO) and cuckoo search (CS) algorithm have been extensively employed for parameter tweaking and model optimisation. Although CS has been extensively applied in the fields of image processing, financial data prediction, etc. its application in the evaluation of civic and political education is especially not yet common in the field of education due of its stochastic wandering approach based on Levy flights and strong ability to jump out of the local optimum (Sharma et al., 2021). By using CS to the civic education assessment model, the limits of the model from becoming local optimality during the training process can be essentially avoided and the model will have more global search power.

Extreme learning machine (ELM) has strong generalisation performance and fast training speed (Ding et al., 2015), which helps to show good application potential in the field of educational assessment. ELM has been found to learn rapidly in classification and regression tasks; nevertheless, its starting parameters' unpredictability causes it to demonstrate instability on complicated datasets and is prone to local optima. Some research on the potential of particle swarm algorithms and GAs to maximise ELM models in recent years has revealed modest effects of optimisation.

This work uses CS to optimise the ELM and modifies the ELM's starting values by means of global search capabilities of CS, therefore enhancing the flexibility and prediction accuracy of the model on challenging data. This work offers the following novelties:

1 Combining CS to optimise the ELM model: This work initially aggregates CS with ELM and employs the CS algorithm to optimise the input weights and biases in the ELM model, so increasing the prediction accuracy of the model. By means of an intelligent optimisation mechanism, the approach greatly enhances the performance of the conventional ELM model and shows great applicability and accuracy in ideological and political teaching quality evaluation.

2 Multi-dimensional and multi-level assessment framework: To fully evaluate the efficacy of ideological and political education in colleges and universities from several angles, the assessment model suggested in this work uses a three-layer structure of aim layer, criterion layer, and element layer. With great theoretical merit and practical relevance, the framework of this study can more fully and precisely reflect the teaching quality than the conventional single-dimensional assessment approach.

3 Innovative use of experimental data: Highly representative and practically useful, the dataset used in this article consists on the ideological and political teaching effectiveness evaluation data of a university from 2008 to 2017. By means of standardisation of this dataset and indicator score computation, this paper not only offers a fresh research viewpoint for the assessment of ideological and political teaching in colleges and universities but also offers important empirical data support for research in allied domains.

4 Improved model assessment indicators: This work uses the correlation coefficient (R) and the root mean square error (RMSE) as assessment indicators to evaluate the whole performance of the model. These indicators combine the accuracy and stability of prediction to give educational managers a more objective and scientific approach of evaluating the performance of the model and so improving the practical application value of the model.

2 Relevant technologies

2.1 CS algorithm

Based on cuckoos' parasitic breeding habits in nature, CS is an optimising method (Rajabioun, 2021). Combining the Levy fly stochastic wandering mechanism to get effective exploration of the solution space through global search, the algorithm uses the cuckoo's tactic of laying its eggs in other birds' nests. The proposed civic education assessment model uses the CS method to optimise the initial ELM parameters so enhancing the generalisation capacity and prediction accuracy of the model.

First, the CS algorithm generates a random set of candidate solutions – that is, a random set of bird's nest sites in the solution space – and assesses the fitness of every bird's nest site (Cuong-Le et al., 2021; Elkeran, 2013). Here the candidate solutions match the ELM model's parameter combinations. The CS method aims to make the model fit the intricate civic education data with improved parameter combinations throughout several screening and optimisation runs, therefore enabling better assessment of the ideological and political character of pupils.

The prediction error of the model defines the fitness of every candidate solution in the following sense:

$$f(x) = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2 \tag{1}$$

The aim of the method is to minimise this inaccuracy where N is the number of samples, y_i is the actual value and $\hat{y}_i$ is the projected value.

The Levy flight, a stochastic wandering technique following a Levy distribution that produces step sizes for long jumps to enable more thorough global search (Viswanathan et al., 2008), is the fundamental mechanism of the CS algorithm. One may obtain the Levy flight's step size by means of the following equation:

$$L \sim Levy(\lambda) = t^{-\lambda}, 1 < \lambda \leq 3 \tag{2}$$

The step size is then updated using the following equation:

$$x_i^{t+1} = x_i^t + \alpha \cdot L \cdot \left(x_i^t - x_j^t\right) \tag{3}$$

With α as the step scaling factor, x_i^t and x_j^t correspondingly represent the locations of the i^{th} and j^{th} nests at the t^{th} iteration. x_i is the ELM model parameter vector in the civic education assessment model. Through extensive parameter space exploration, this method helps to prevent the algorithm from converging into local optimal solutions.

Based on the Levy flight, the CS algorithm creates a fresh solution in every iteration, compares it with the present solution, and chooses the most suited one for storage. Particularly, the new answer is produced by means of the following equation:

$$x_{new} = x_{current} + \beta \cdot L \cdot \left(x_{best} - x_{current}\right) \tag{4}$$

where x_{best} is the current solution with the best fitness and β is the step scaling factor. The comparison of the new and current solutions follows this procedure:

$$x_i^{t+1} = \begin{cases} x_{new}, & \text{if } f\left(x_{new}\right) < f\left(x_i^t\right) \\ x_i^t, & \text{otherwise} \end{cases} \tag{5}$$

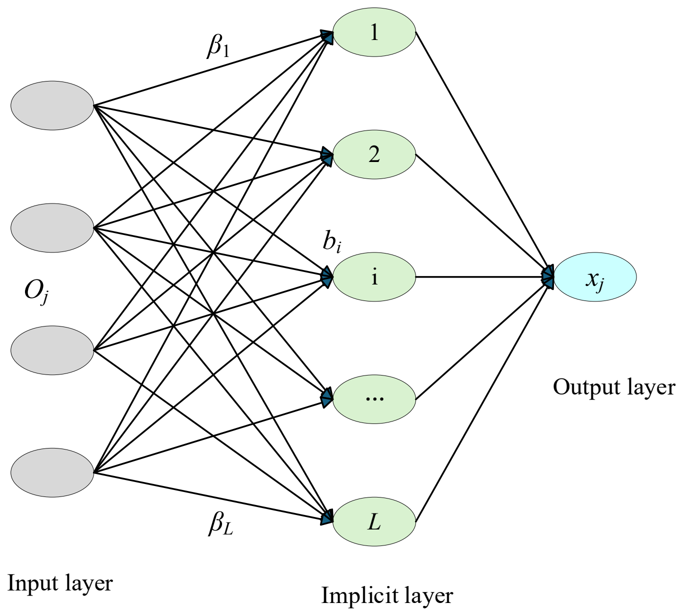
This choice and elimination system guarantees the slow convergence of the optimal solution of the algorithm and enhances the accuracy and robustness of the model.

Following the set maximum number of iterations or satisfying the error threshold, the CS algorithm will halt the optimisation and subsequently acquire the optimal parameter combinations which are further used to improve the ELM model.

2.2 Extreme learning machine

The basic concept of ELM, a fast learning technique for single hidden layer feed-forward neural network (SLFN), is to randomly generate the weights and biases of the hidden layer (Huynh et al., 2008), then use the least squares approach to rapidly compute the output weights to attain efficient learning, see Figure 1. This work builds an evaluation model for the calibre of political and ideological instruction given to college students using ELM.

Figure 1 Structure of ELM (see online version for colours)



Assume we have a training set (X_i, Y_i) comprising N training samples whereby X is a $n \times Q$ dimensional input matrix and Y is a $m \times Q$ dimensional output matrix. One can articulate the ELM model's output as:

$$\sum_{i=1}^{L} \beta_i g(W_i \cdot X_i + b_i) = o_j, \; j = 1, 2, \ldots, N \tag{6}$$

where W_i is the input weight; β_i is the output weight of the i^{th} hidden layer node; $g(x)$ is the excitation function; b_i is the bias of the i^{th} hidden layer node; o_j is the output value of the model for the j^{th} sample. This formula explains how the ELM model's output nodes move input data to the output space to generate the model's projected values.

In order to optimise the model, the goal of ELM is to minimise the output error of the model, i.e.,

$$\sum_{j=1}^{N} (o_j - t_j)^2 = 0, \; j = 1, 2, \ldots, N \tag{7}$$

where t_j is the j^{th} sample's real output.

ELM shows the link between inputs and outputs in the model computation by use of the implicit layer's output matrix H. The formula of ELM allows one to express the output weights in matrix form:

$$H\beta = T \tag{8}$$

where T is the goal output matrix; H is the hidden layer nodes' output matrix; β is their output weight matrix. The least squares approach allows one to formulate the ideal solution of the output weight β:

$$\hat{\beta} = H^{\dagger} T \tag{9}$$

where $H^{\dagger}$ is the Moore-Penrose generalised inverse of matrix H. Computational efficiency is where the ELM model clearly shines.

Although the ELM model clearly improves computational efficiency, the randomly generated implicit layer weights W_i and bias b_i could lead the model to collapse into the local optimal solution (Song et al., 2020), so influencing the correctness and stability of the final evaluation. This work uses CS to tune the initial ELM settings in order to address this challenge. Especially, the CS method maximises the model's output error function by:

$$f(W, b) = \sum_{j=1}^{N} \left(o_j - t_j\right)^2 \tag{10}$$

The objective is to determine the ideal W and b by minimising this error function, where $f(W, b)$ is an error function dependent on the present parameters W and b and o_j and t_j are the model output and true output values respectively.

3 Assessment model of civic education based on CS-ELM

3.1 Model construction

This work presents a CS-ELM-based evaluation model for civic education with three layers: the objective layer, the criterion layer, and the element layer. The element layer sets the input features of the model; the target layer is the last output of the model; the criteria layer determines the weights of every evaluation index. Combining multi-dimensional data inputs with the CS optimisation technique, the model is developed with the intention of precisely evaluating the ideological and political character of college students, see Figure 2. We shall layer by layer introduce the model construction method.

3.1.1 Objective layer

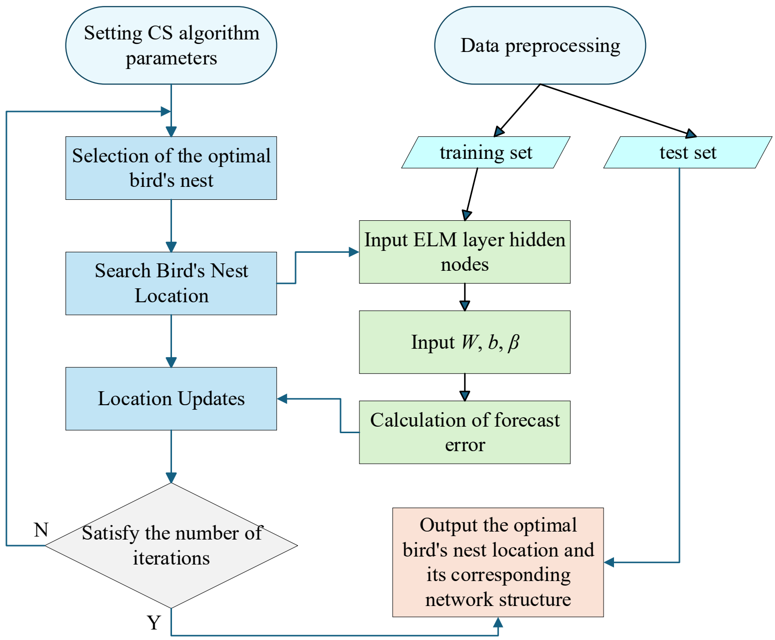
Defining the ultimate aim of the evaluation of civic education – a thorough assessment of students' ideological and political quality – the objective layer is the core of the concept (Boritz, 2005). Covering elements of several dimensions such philosophy and morals, political attitude, and behavioural performance, this layer concentrates on the general framework of the assessment.

One can represent the model's output by means of the following formula:

$$O = f(W \cdot X + b) \tag{11}$$

where X is the input feature matrix; W is the weight matrix; b is the bias term; f is the activation function, either sigmoid or ReLU, for nonlinear mapping; O is the output of the model, which shows the assessment results of the ideological and political quality of college students.

Figure 2 Structure of CS-ELM (see online version for colours)



3.1.2 Criterion layer

The weight and significance of every evaluation indication are ascertained from the criterion layer. The criterion layer must take into account several dimensions of ideological and political quality (such as ideological attitude, emotional elements, behavioural performance, etc.), per the multidimensional evaluation needs, according to principal component analysis (PCA) can help one to extract these dimensions and get the weight of every dimension (Abdi and Williams, 2010). Assuming that every dimension's weight is $w_1, w_2, \ldots, w_n$, the criterion layer can be stated as follows:

$$C = \sum_{i=1}^{n} w_i \cdot x_i \tag{12}$$

where x_i is the score of the i^{th} evaluation indicator and C is the whole assessment outcome. The criterion layer's goal is to weight and combine the dimensions to get an all-around evaluation result.

3.1.3 Element layer

First we must define the input features clearly and optimise the ELM's implicit layer bias and input weights by CS in the building of the element layer. Through multi-dimensional data extraction and processing, the element layer's main goal is to offer rich information support for the model so improving its predictive and generalisation capacity.

Assumed to be $N \times M$ dimensional is the input feature matrix X, where N is the sample count and M is the feature dimension of every sample. The CS system is proposed to optimise the weights and biases of the input layer thereby improving the accuracy and efficiency of the ELM model. The CS is able to avoid entering the local optimal solution by modelling the parasitic breeding behaviour of cuckoos and combining with the Levy flight strategy, thereby obtaining the global optimal solution and optimising the performance of the ELM.

The CS method changes every weight and bias using the following update guidelines to maximise these values:

$$W_i^{(t+1)} = W_i^{(t)} + \alpha \cdot \left(W_i^{(t)} - W_{best}^{(t)} \right) + \delta_i \tag{13}$$

$$b_i^{(t+1)} = b_i^{(t)} + \alpha \cdot \left(b_i^{(t)} - b_{best}^{(t)} \right) + \delta_i \tag{14}$$

The step factor is α; the random disturbance produced by Levy flight is δ_i; the weights and bias of the present optimal solution are W_{best} and b_{best}, respectively. By means of several rounds, the CS algorithm continuously optimises the initial weights and biases of the ELM, therefore enabling the model to better fit to complicated data features and raise prediction accuracy.

Following the completion of input feature optimisation, the model can produce target layer outcomes of students' ideological and political quality assessment. The final model output can be stated using the following formula considering the influence of every input feature and weight optimisation:

$$O_{final} = \sum_{i=1}^{n} w_i \cdot O_i \tag{15}$$

O_{final} is the final ideological and political quality assessment result; w_i is the associated weight; O_i is the output of every sub-model, e.g., sentiment analysis, behavioural analysis, etc.

By means of exact construction and elemental layer optimisation, the model is able to fully integrate the multi-dimensional information and so enhance the correctness and dependability of the evaluation. The approach of CS optimisation of ELM offers an effective global search technique, which enhances the generalisation capacity and adaptability of the model in challenging tasks even more.

3.2 Assessment metrics

Selecting suitable evaluation criteria is absolutely vital while assessing the performance of a model. In the prediction task, reasonable assessment indicators can efficiently show the stability and correctness of the model. In this work, RMSE and R are chosen as the key assessment criteria for the CS-ELM-based ideological and political education assessment model built here. These two metrics offer a good base for model optimisation and tuning and may fully show the predictive capacity of the model.

On the one hand, RMSE is a widely used metric to evaluate actual against projected values; its computation formula is:

$$RMSE = \sqrt{\frac{1}{N} \sum_{j=1}^{N} \left(o_j - t_j \right)^2} \tag{16}$$

where o_j is the expected model value; t_j is the actual value; N is the sample count. The smaller the value indicates the smaller the model prediction error; RMSE can more naturally show the correctness of the model prediction outcomes.

Second, the formula is R to determine the linear link between the actual and expected values of the model (Krzywinski and Altman, 2015).

$$R = \frac{\sum_{j=1}^{N}(o_j - \bar{o})(t_j - \bar{t})}{\sqrt{\sum_{j=1}^{N}(o_j - \bar{o})^2 \sum_{j=1}^{N}(t_j - \bar{t})^2}} \tag{17}$$

where $\bar{o}$ and $\bar{t}$ respectively are the average of the expected and real values. The range of the correlation coefficient is [–1, 1]. A strong positive correlation between the model prediction and the real value indicates that the prediction impact is better when its value is near to 1.

4 Experimental results and analyses

4.1 Data source

The evaluation data of the efficacy of ideological and political education in a university from 2014 to 2023 provides the data used in this paper. Raw data were first standardised and normalised using the maximum value approach therefore guaranteeing their comparability. By means of a comparison between each evaluation indication two by two, the 1–9 scale technique [10–11] was specifically applied to compute the scores of the evaluation indicators of ideological and political teaching effectiveness in colleges and universities and the final teaching effectiveness score. Tables 1 and 2 contain comprehensive information on the final score as well as the scores of every evaluation index.

Table 1 Score of civics teaching effectiveness evaluation indicators

Index no.	*2014*	*2015*	*2016*	*2017*	*2018*	*2019*	*2020*	*2021*	*2022*	*2023*
1	0.022	0.032	0.045	0.057	0.060	0.060	0.097	0.106	0.135	0.146
2	0.111	0.121	0.149	0.169	0.148	0.131	0.179	0.169	0.205	0.211
3	0.165	0.175	0.179	0.183	0.189	0.196	0.197	0.243	0.254	0.286
4	0.164	0.185	0.195	0.197	0.204	0.204	0.247	0.253	0.261	0.260
5	0.218	0.239	0.215	0.188	0.166	0.155	0.157	0.157	0.277	0.286
6	0.049	0.048	0.053	0.072	0.102	0.106	0.131	0.165	0.184	0.189
7	0.036	0.037	0.042	0.055	0.080	0.109	0.138	0.159	0.175	0.218
8	0.055	0.055	0.054	0.068	0.082	0.091	0.103	0.102	0.113	0.116
9	0.033	0.051	0.074	0.070	0.066	0.075	0.092	0.094	0.089	0.102
…	…	…	…	…	…	…	…	…	…	…
24	0.06	0.017	0.060	0.058	0.061	0.058	0.058	0.083	0.111	0.145
25	0.109	0.131	0.121	0.102	0.042	0.046	0.060	0.072	0.089	0.112
26	0.009	0.012	0.015	0.023	0.035	0.038	0.051	0.065	0.087	0.114

Table 2 Final of civics teaching effectiveness evaluation

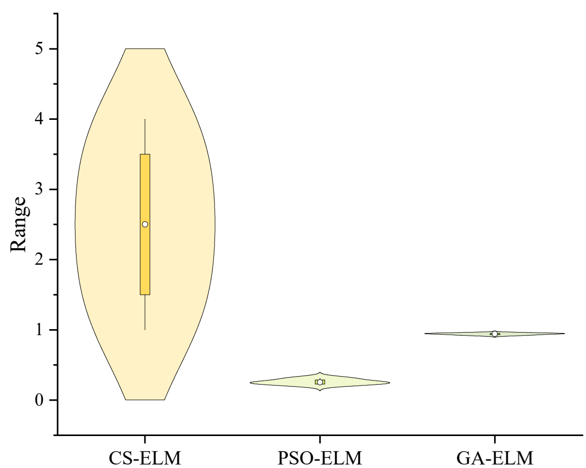
Year	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Score	1.543	2.508	3.515	3.519	4.539	4.615	4.693	4.805	4.884	4.994

4.2 Experimental procedure

In this study we conducted a comparison experiment, an ablation experiment, and a time consumption comparison experiment to measure the framework in layers.

First this work compares ELM models mixed with various optimisation techniques – more especially, PSO-ELM, GA-ELM, and conventional ELM models. These comparison models cover typical optimisation techniques, among which PSO and GA, classical population intelligence optimisation methods, have a great competence in parameter optimisation, while the standard ELM model performs no optimisation. These comparison studies let one evaluate the benefits of CS-ELM above alternative models. Figure 3 displays the experimental outcomes.

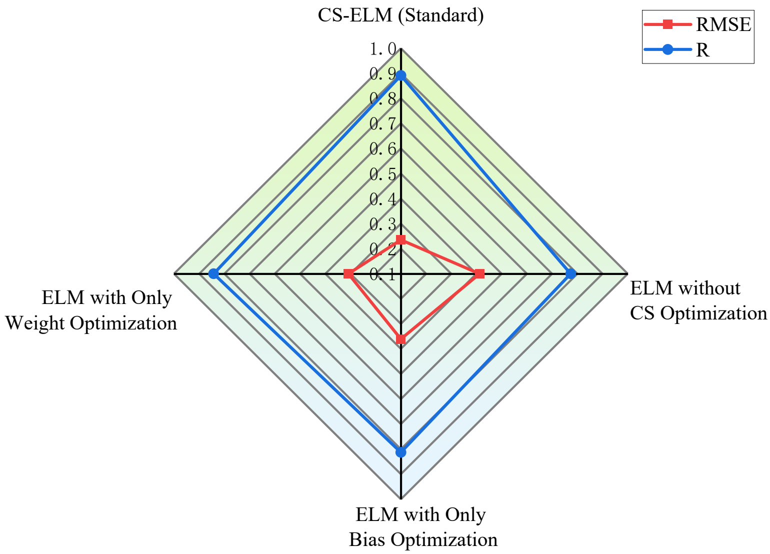
Figure 3 Comparative experimental results (see online version for colours)



The CS-ELM model is able to more precisely evaluate the impact of students' ideological and political education since, as the figure shows, it performs the best among all the compared models has the lowest error in the RMSE value and the highest correlation coefficient R value. Furthermore, whilst PSO-ELM and GA-ELM are likewise better than conventional ELM, CS-ELM has more notable optimising impact in comparison.

Analysing the contribution of every component of the model to the final evaluation impact came next in the ablation experiment. We gradually eliminate or alter important components in the model to reach this aim and track the effects on the model performance. We first conducted typical experiments using the baseline CS-ELM model. We then create numerous varying layouts to assess how each component affects model performance. To evaluate the function of the CS optimisation approach in enhancing model performance, we initially eliminated it and trained and tested straight with the conventional ELM model. Under this arrangement the model's biases and input weights are randomly initialised rather than optimised. After eliminating the input weight optimisation, we then further remove the bias portion to assess the model performance just on that basis. This arrangement enables us to assess the contribution of optimal input weight to the model. Figure 4 shows the experimental outcomes.

Figure 4 Results of ablation experiment (see online version for colours)



The findings of the ablation studies reveal very diverse effects of various configurations on the model performance. First of all, along with the CS optimisation technique, the standard CS-ELM model shows a notable increase in model correctness and stability while demonstrating best RMSE and correlation coefficient R. This confirms the efficiency of the CS optimisation method resulting from the choice of input weights and biases, hence improving the model prediction performance.

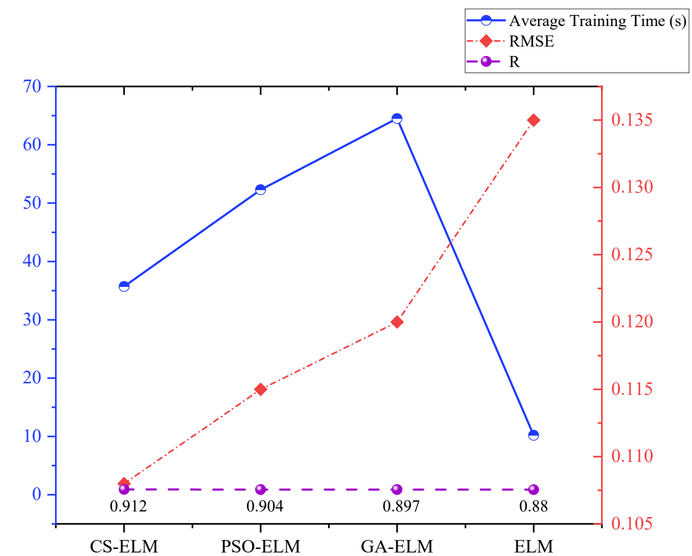
In the other setups, the conventional ELM model without CS optimisation shows a greater RMSE and a poorer correlation coefficient R, meaning that randomly initialising the weights and biases influences the model's prediction accuracy, hence producing undesirable outcomes. Though both are better than the unoptimised configuration, the bias-only optimised configuration is rather less effective than the weight-only optimal configuration. This implies that whilst the effect of weight optimisation may be more significant, bias and weight optimisation independently help to improve model performance.

Our aim in the time-consumption comparison studies is to assess the operational efficiency of the CS-ELM models in order to ascertain their relevance in practical uses. Initially, we arranged the experimental circumstances in the same hardware environment such that every model ran using the same number of hidden layer nodes and training dataset size. This homogeneous arrangement allows us to evaluate, under comparable circumstances, the training time consumption of several models. We selected four models for the tests – the CS-ELM, PSO-ELM, GA-ELM, and conventional ELM models. Every model's overall training time to convergence was noted from initialisation and each experiment was repeated three times to get steady average time consumption data.

We next evaluated the trade-off between time and accuracy by aggregating the time consumption findings of every model combined with its accuracy measures (RMSE and R-value). In the comparison, we especially focus on whether the CS-ELM model preserves high accuracy while displaying great computational economy. By means of detailed comparison of the time consumption of several models, this experiment offers a foundation for the performance benefits of the CS-ELM model in pragmatic applications.

Figure 5 displays the last experimental results with lists of average training times, RMSE and R-value for every model to help to observe the time efficiency advantage of CS-ELM.

Figure 5 Experimental results of time consumption comparison (see online version for colours)



In terms of accuracy and maintains a high computational efficiency in terms of time consumption, the experimental findings reveal that the CS-ELM model beats the other evaluated models. While CS-ELM achieves a better balance between time and accuracy than PSO-ELM and GA-ELM, the optimisation process of CS-ELM somewhat increases the time consumption but brings far greater accuracy improvement than that of the conventional ELM model. In general, in useful applications the CS-ELM model is quite dependable and practical.

5 Conclusions

In this work, we offer a CS-ELM model applied to evaluate political and ideological education in institutions of higher learning. The accuracy and stability of the assessment model can be very much enhanced by including the CS method to maximise the ELM model. In this paper, CS is combined with ELM for the first time and the CS algorithm is used to optimise the input weights and biases in the ELM model. Particularly in terms of assessment accuracy and convergence time, the experimental results reveal that the

CS-ELM model shows greater performance than the conventional ELM and other optimisation methods in numerous trials.

This study produces some findings, however there are still certain limits. First of all, the quality of the data, the sample size, and the feature selection could still influence the performance of the CS-ELM model on high-dimensional data and complicated datasets even although most of the studies show good performance of the model. Second, although the CS optimisation technique may efficiently avoid local optimal solutions, the computational complexity and time consumption of the algorithm may create a bottleneck preventing the application of the model in the face of bigger scale data. At last, this study mostly addresses the application in the sphere of ideological and political education; so, greater analysis of the universality and extensibility of the model is necessary by validation in other pragmatic situations.

Future study can be strengthened and enlarged in the following areas to overcome the constraints of the present one:

1 Ability to handle high-dimensional and complex data: When confronted with high-dimensional data, particularly in scenarios involving more feature dimensions, the currently investigated models could exhibit computational bottlenecks. To fit bigger and more complicated datasets, it can be coupled with dimensionality reduction methods or more effective feature selection algorithms in the future to lower the computational complexity while preserving the prediction accuracy of the model.

2 Improvement of model generalisation ability: The diversity and representativeness of the training data define the current model generalisation capacity; however, future improvement of this capacity can be achieved by increasing the dataset with data from other areas and varied educational background. Furthermore, investigating more techniques of data improvement will help the model to be more flexible in several surroundings.

3 Ability to handle unstructured data: Although the current paradigm is mostly suited for organised data, unstructured data – such as student open-ended evaluations, sentiment analysis, etc. – also plays a significant part in pragmatic applications. We can investigate in the future how to include unstructured data – text analysis and attitude analysis – into the model and so enable the model to more fully represent the ideological and political situation of students.

Future study in these domains is projected to overcome current constraints, progress the field of educational evaluation, and give educational managers more accurate and complete decision assistance by means of additional exploration in these areas.

Declarations

All authors declare that they have no conflicts of interest.

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