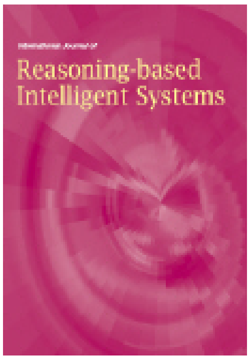

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Real-time effectiveness evaluation of online education based on LSTM-transformer model

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Abstract: Online education, with its flexibility, has become an integral part of the education sector. To address the challenges posed by existing research, which struggles to capture spatio-temporal locality and handle lengthy historical evaluation sequences, this paper first inputs historical evaluation data into a long short-term memory network (LSTM) to discover long-term sequential relationships in the evaluation data. The LSTM's output is then fed into the Transformer encoder, followed by an encoding layer that feeds into the transformer layer, where multi-head attention mechanisms enhance concurrent learning of long-term dependencies. Second, the final evaluation prediction results are obtained through a softmax output. Finally, an improved Bayesian optimisation algorithm is used for hyperparameter iteration, and the optimal hyperparameters for the evaluation model are selected. Experimental outcome demonstrates that the average evaluation accuracy of the proposed model has improved by 5.98%–12.24%, validating the efficiency of the proposed model.

Keywords: online education; spatial layout; effectiveness evaluation; LSTM model; transformer model; Bayesian optimisation.

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1 Introduction

Driven by the continuous momentum of the digital technology wave, online learning has quickly emerged as a key component of worldwide education, thanks to its significant advantages such as breaking through time and space constraints and convenient resource sharing. How to accurately and efficiently evaluate the real-time learning effectiveness of learners in online education scenarios has become a core issue to be solved (Castro and Tumibay, 2021). Traditional methods for evaluating the effectiveness of online education are difficult to capture the dynamic changes in the learning process. These methods not only fail to provide timely feedback on the learners' learning status, but also struggle to adapt to the personalised and real-time teaching needs of online education (Alemayehu and Chen, 2023). With the successful application of deep learning technology, introducing artificial intelligence algorithms into the online education evaluation system has provided a new technical approach to solving the above problems. Although some studies have attempted to apply deep learning to online education evaluation, most of them are limited to the application of a single model and have not fully leveraged the complementary advantages of different models (Dias et al., 2020). Accordingly, in-depth investigations into hybrid deep learning applications for real-time performance measurement in online education are practically meaningful for driving its high-quality advancement.

Altuwairqi et al. (2021) processed students' login information in online learning systems and used various classification methods to analyse and predict students' evaluation behaviour. Ogange et al. (2018) designed an online education effectiveness evaluation method using the ARIMA model, constructing a prediction model by analysing historical student evaluation data. Ren et al. (2017) chiefly adopted factor analysis methods when analysing the norms affecting the effectiveness of classroom education and pedagogy, and through the use of multiple linear regression technology, they discovered valuable indicator patterns. Villegas-Ch et al. (2021) analysed students' grades using the Hadoop platform and optimised the standard Apriori algorithm through integration with MapReduce's computational paradigm, analysing the correlation between students' performance across different courses and examining how curriculum design affects academic outcomes, thereby extracting actionable insights to inform pedagogical improvements and enhance educational quality. Rong (2022) first applied decision tree analysis to online teaching effectiveness data to create an optimal prediction model. She then conducted verification and comparative analysis using association rule mining to evaluate the model's dependability.

The models based on traditional time series prediction follow specific distributions or linear relationships, while machine learning models can automatically capture high-dimensional, nonlinear, and interactive complex patterns. However, they rely on manually extracted features, resulting in low efficiency in evaluating online education effectiveness. Due to the strong feature extraction capability, adaptive learning ability, and nonlinear processing capability of deep learning, researchers have constructed a series of deep learning-based online education evaluation models. By introducing neural network principles to online education quality evaluation, Zhang (2021) first established mathematical models, then quantified all indicators, and finally constructed a BP neural network model that generated relatively reliable evaluation outcomes. Zhang (2024) developed a wavelet neural network-based mathematical framework for online education assessment, demonstrating significant enhancement in teaching evaluation accuracy. Mumtaz et al. (2024) proposed a multi-scale CNN to mine multi-dimensional data features of in-school education, enhancing the effectiveness of educational evaluation. Jeong and Cho (2023) proposed an online education effectiveness evaluation model based on recurrent neural networks (RNN), achieving an evaluation accuracy of 80.4%. However, RNN faces the problem of gradient disappearance, which limits its capability to study long-term relations in educational big data. LSTM effectively overcomes this problem by introducing a gating mechanism, achieving precise control over information flow and update. Jiao (2024) used the BERT model to generate dynamic vectors of teaching texts, then input the vectors into LSTM for teaching quality assessment, achieving a classification accuracy of 81.42%. Zhang and Yang (2024) used CNN to extract local features of online education evaluation texts, and used LSTM to extract global features. By concatenating and fusing global and local features, the evaluation accuracy was improved.

The Transformer architecture fundamentally relies on attention mechanisms as its core operational principle, discarding the cyclic structure and convolution structure of traditional RNN and CNN, achieving parallel computing and significantly improving computational efficiency. Xiong et al. (2024) introduced a multi-scale Gaussian prior to improve the transformer's local feature capture capability, while also proposing an orthogonal regularisation technique to prevent redundancy in the multi-head self-attention mechanism. Venkateshwarlu et al. (2024) used empirical mode decomposition to decompose online education evaluation indicators, and extracted features from the decomposed indicators through the Transformer. They used a fully connected network to output the online education evaluation results. The results show that the proposed model outperforms the baseline model in mean absolute error (MAE) and root mean squared error (MSE) metrics. Zhang (2025) used the flexible integration of the transformer model and attention mechanism to achieve synchronous feature extraction of evaluation sequence information in the two dimensions of course and time, and obtained the evaluation of online education effectiveness through softmax.

In previous work, single LSTMs, transformers, and traditional hybrid approaches exhibited significant limitations. Single LSTMs rely on chain memory units to process temporal information. While they can capture long-term sequence dependencies, they lack sufficient focus on locally critical information and suffer from long-term dependency gradient decay. Single transformers rely on global self-attention to model sequence associations. While enabling parallel computation and focusing on local critical information, they exhibit weak modelling capabilities for temporal coherence in long sequences, and their computational complexity increases quadratically with sequence length. Traditional hybrid approaches often employ a functionally decomposed serial connection, lacking information exchange between LSTMs and transformers. This prevents the synergistic optimisation of temporal memory and attention mechanisms.

Scholars worldwide have developed various evaluation models for assessing the effectiveness of online education. However, as the digital transformation of education deepens, these models have gradually revealed core shortcomings: narrow evaluation dimensions, superficial data utilisation, limited model adaptability, and a lack of practical closure. These deficiencies make it difficult for the models to align with the essential characteristics of online education. Namely, its dynamic nature personalised learning experiences, and complex scenarios. In addition, these studies are difficult to capture spatiotemporal locality and lack the introduction of algorithm parameter tuning, which leads to an inability to achieve global control, greatly slowing down the forward inference and training efficiency of the algorithm. To this end, this paper puts forward an online education real-time effectiveness evaluation model based on the LSTM-transformer model. The model not only includes a specific spatiotemporal feature embedding method for online education evaluation texts to extract high-quality spatiotemporal feature vectors, but also integrates a high-order feature interaction module, as well as a spatiotemporal embedding and real-time effectiveness evaluation module. After spatiotemporal feature embedding, the model will fuse various features to form an enhanced feature set, which is then input into the feature interaction module. The feature interaction module combines LSTM and Transformer, where the former captures long-term time dependencies, and the latter identifies key items in the sequence and self-adaptively adjusts. After processing by this module, the model can generate accurate real-time effectiveness evaluation results for online education. Finally, a random forest improved Bayesian optimisation algorithm (RFBO) is designed. RFBO trains the LSTM-transformer model as a local user model, and after the model fusion completes hyperparameter optimisation, the best hyperparameters are selected. The local user model then trains the fused model with the best hyperparameters, thus improving the prediction accuracy of online education effectiveness evaluation. Experimental results show that the coefficient of determination R^2 of the proposed model is improved by 0.73%–1.3% compared to the baseline model, which can achieve more accurate real-time effectiveness evaluation of online education.

2 Relevant theoretical foundations

2.1 Long short-term memory network

As an improved variant of RNNs, LSTM's core advantage lies in its systematic resolution of the gradient vanishing/exploding problem inherent in traditional RNNs through its gating mechanism and cell state design, while significantly enhancing its modelling capabilities for long-term sequence dependencies. The LSTM model, a distinct RNN architecture, excels at handling sequential data and overcoming the vanishing gradient problem in long sequences. Compared with traditional RNN, LSTM introduces a memory cell and gate mechanism, enabling the network to model long-range dependencies more effectively. The defining components of LSTM networks are their cell states and gate structures. The LSTM architecture incorporates dedicated memory cells that preserve and propagate information across time steps through regulated operations, effectively preventing the information degradation observed in conventional RNNs (Wen and Li, 2023). Meanwhile, the LSTM architecture regulates information flow through three distinct gating mechanisms: the input gate, forget gate, and output gate, which collectively determine the retention and propagation of temporal information. The gating mechanisms employ tanh activation functions to compute element-wise products between input signals and memory cell states, generating normalised outputs that precisely regulate information propagation through the network.

LSTM model dynamically adjusts the content of memory by introducing these gate mechanisms and the state of the memory cell. First, the input gate governs both the incorporation of current input data and the subsequent modification of the memory cell state. Then, the forget gate regulates the extent to which prior memory contents are preserved or discarded from the cell state. Finally, combining these two parts of information, the updated memory cell state is obtained. The LSTM architecture successfully addresses the vanishing/exploding gradient problems inherent in conventional RNNs through its gated memory cell mechanism, which maintains stable gradient flow during backpropagation, and can better model long-term dependencies, achieving significant performance improvements in many sequence-related tasks (Zhang et al., 2020).

2.2 Transformer model

Employing scaled dot-product attention as its core operation, the transformer architecture achieves state-of-the-art performance in sequential data processing tasks without recurrent connections (Nassiri and Akhloufi, 2023). Compared with traditional RNN and CNN, the transformer architecture demonstrates exceptional capability in handling extended sequence lengths and modelling long-term dependencies through its self-attention mechanism. The fundamental innovation of the Transformer architecture lies in its self-attention mechanism, which dynamically establishes pairwise relationships between all sequence positions and utilises these inter-positional dependencies for contextualised representation learning.

The conventional Transformer architecture comprises two primary components: an encoder stack for input processing and a decoder stack for output generation. The encoder transforms the input sequence into a set of high-level abstract characteristics, whereas the decoder leverages these characteristics to produce the related output sequence (Liu et al., 2021). The encoder and decoder modules both employ deep stacks of identical structural levels, with each level progressively refining the representation. Every level integrates two fundamental components: a multi-head attention module (MAM) for contextual relationship modelling followed by a position-wise feedforward network (FPN) for characteristic transformation. The FPN performs nonlinear feature transformation through learned affine transformations and activation functions, mapping inputs to higher-dimensional representations. The MAM enables simultaneous self-attention operations across multiple representation subspaces, facilitating the capture of diverse semantic relationships within the input. The attention mechanism of the transformer is expressed as follows, in which Q, K, V are the query matrix, key matrix, and value matrix, individually; W_i^Q, W_i^K, W_i^V are all parameter matrices.

$$MutiHead(Q, K, V) = Concat\left(head_1, head_2, ..., head_n\right)W^o \tag{1}$$

$$head_n = Attention\left(QW_i^Q, KW_i^K, VW_i^V\right) \tag{2}$$

The transformer incorporates positional encoding to inject sequential order information into the model, enabling it to discern positional relationships within otherwise permutation-invariant attention operations. Positional encoding is implemented through the element-wise addition of deterministic vector representations to corresponding sequence positions in the input embeddings. The position encoding calculation method of the transformer is as follows, where c is the position encoding matrix obtained through the position encoding operation, i is the dimension index, pos is the position index; d_{mod} is the input dimension.

$$PE_{(pos, 2i)} = \sin\left(pos / 10{,}000^{2i/d_{\text{mod}}}\right) \tag{3}$$

$$PE_{(pos,2i+1)} = \cos\left(pos / 1{,}000^{2i/d_{\text{mod}}}\right) \quad (4)$$

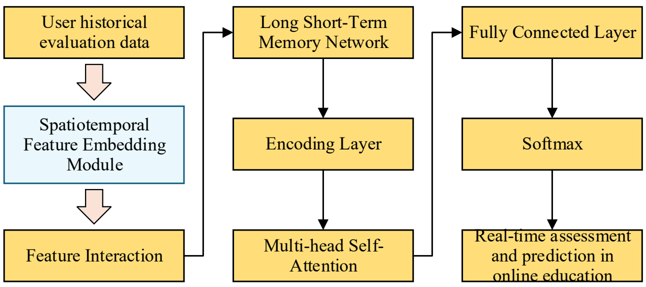
Transformer fundamentally resolves the core challenges faced by RNNs and CNNs in sequence modelling. Namely, long-range dependencies and training efficiency, through their unique self-attention architecture and parallelised design. This has established them as the dominant architecture across multiple fields today, including natural language processing and computer vision.

3 Real-time effectiveness evaluation of online education based on the LSTM-transformer model

3.1 Overall framework of the evaluation model

Real-time performance evaluation of online education is an important task in time series prediction, usually involving feature extraction from sequence data, especially spatiotemporal features, and then time modelling to adapt to long-term prediction needs. To address the shortcomings of existing models in time series modelling and capturing long-range dependencies, this paper suggests a real-time performance evaluation approach for online education in light of the LSTM-Transformer model. The method first extracts the embedding vectors of spatiotemporal features, then performs interactive modelling of spatiotemporal and user factors, and finally generates the prediction results. Figure 1 shows the process of this prediction model.

Figure 1 Real-time effectiveness assessment process for online education (see online version for colours)



The model not only includes a specialised spatiotemporal feature embedding method for online education evaluation text to extract high-quality spatiotemporal feature vectors, but also integrates a high-order feature interaction module, as well as a spatiotemporal embedding and real-time performance evaluation module. After spatiotemporal feature embedding, the model will fuse various features to form an enhanced feature set, which is then input into the feature interaction module. The feature interaction module combines the LSTM and the multi-head self-attention mechanism, where the former maintains inter-temporal connections across distant intervals, and the latter identifies key items in the sequence and adaptively adjusts. After processing by this module, the model can generate accurate real-time performance evaluation results for online education.

Input historical online education performance evaluation data into LSTM, then process the data with LSTM to handle long-term dependencies. The output of LSTM is used as input for the position encoding of transformer. Subsequently, the position encoding layer of transformer inputs into the transformer layer, and enhances the concurrent learning of long-term dependencies through the MAM. Ultimately, the linear layer and softmax processing output the final evaluation prediction result.

The goal of this section is to capture long-term patterns by modelling the user's historical evaluation sequence. First, these historical subsequences are connected into an overall trajectory and input into the spatiotemporal embedding module to obtain information about time and spatial relationships. The overall learning trajectory is connected with user embedding to form a comprehensive input. Next, a self-attention module is introduced to generate a series of evaluation behaviour representations, which contain important information at each time point and can capture remote dependencies between different user evaluation behaviours. This is to better understand the patterns and trends in the historical user evaluation behaviour subsequences.

3.2 Spatiotemporal embedding for real-time effectiveness evaluation of online education

To effectively represent user learning behaviour, this paper introduces L to indicate the stay location embedding matrix. For learning intervals, first convert them into a tuple, T to represent the time embedding matrix. In the absence of additional user information, this paper uses the user embedding matrix U to represent differences between users. Where M is the amount of users, and d is the dimension of the embedding vector. Through user embedding, the similarity between users can be captured, and personalised user needs can be considered when evaluating educational effectiveness. During the feature processing, the dimensions of all features after embedding remain consistent. This standardised dimension is to ensure that in the subsequent feature interaction module, outer product calculations can be directly performed without introducing additional operations to align their dimensions due to dimension mismatches, which would increase computational complexity and model complexity. Therefore, maintaining consistency in embedding dimensions is very important for improving model performance and efficiency.

There are many methods for embedding initialisation. Word2Vec (Jang et al., 2019), as a classic word embedding model, has a pioneering significance in the field of pre-trained language models. Although more complex models such as BERT and GPT have emerged later, Word2Vec still has unique advantages in specific scenarios due to its simplicity, efficiency, interpretability, and low resource consumption. As a classic word vector model, Word2Vec demonstrates advantages of low complexity, high speed, and easy deployment in text embedding evaluation. Its core strengths lie in the simplicity of its model architecture, the singularity of its training objective, and the directness of its embedding generation. This stands in stark contrast to the complex architectures, multi-task objectives, and dynamic embeddings of models like BERT and GPT. Ultimately, it achieves a unique advantage in the trade-offs of embedding evaluation performance, particularly well-suited for small-to-medium-sized datasets or real-time embedding scenarios. Initialising user learning behaviour using the pre-training method of Word2Vec is as follows, where l represents the user's learning behaviour. When the pre-training cost is high, random initialisation will not lead to a decrease in performance. By extracting word vectors using the CBOW method as features, the model can better understand the semantic information in the text, thereby more accurately predicting the real-time evaluation effect of online education.

$$\prod_{t=1}^{T} P\left(l^{(t)} \left| l^{(t-m)}, \ldots, l^{(t-1)}, l^{(t+1)}, \ldots, l^{(t+m)}\right.\right) \tag{5}$$

3.3 Feature interaction in real-time evaluation of online education

Existing real-time evaluation models for online education do not consider the higher-order interactions of these vectors. Spatiotemporal locality has a vital effect on the accuracy of educational effect assessment. Empirical evidence demonstrates that direct integration of user and temporal embeddings into the self-attention module yields superior performance compared to post-attention concatenation approaches. Thus, the module for characteristic interaction modelling is required to consider interactions up to the third order, including both second-order and third-order combinations of embeddings. Driven by the cross-learning framework (Semenoglou et al., 2021), this paper stacks feature matrices of three embedded vectors X_0 row by row to convert them into the same shape as X_1 and X_2 through the following equation.

$$X_{h,*}^{1} = \sum_{i=1}^{3} \sum_{j=1}^{3} W_{ij}^{h,1} \left(X_{i,*}^{0} \circ X_{j,*}^{0} \right) \tag{6}$$

$$X_{h,*}^{2} = \sum_{i=1}^{3} \sum_{j=1}^{3} W_{ij}^{h,2} \left(X_{i,*}^{0} \circ X_{j,*}^{0} \right) \tag{7}$$

where $X_{h,*}^{1}$ is the h^{th} row of X_1, the parameter matrices $W^{h,1}$, $W^{h,2}$ represent the second-order and third-order interactions, respectively, and $\circ$ is the Hadamard product. X_1 catches the second-order interaction among any three embedding vectors, while X_2 catches the third-order interaction among any three embedding vectors.

This interaction model is very flexible, allowing new features such as user-interested learning resources to be easily integrated into the network. For n features, the m^{th} interaction can be flexibly expressed as follows. When there are many features, this module allows the order of feature interactions to be flexibly adjusted.

$$X_{h,*}^{m} = \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}^{h,m} \left(X_{i,*}^{m-1} \circ X_{j,*}^{m-1} \right) \tag{8}$$

3.4 Mining user historical evaluation behaviour sequences based on LSTM

After the above spatial-temporal embedding and interaction modules, to further improve the accuracy of online education effect evaluation prediction, it is necessary to mine the regular information in the user's historical sequence. Considering the advantages of RNN in time series problems, but facing the challenges of long-term information retention and gradient disappearance, LSTM is adopted. As an improved version of RNN, LSTM can effectively alleviate these problems while retaining the advantages of RNN. In this task, the matrix U represents the result after processing by the feature interaction layer, where M represents the sequence length. Each input sequence element is calculated through a specific computational process.

$$i_t = \sigma\left(W_{ii} x_t + b_{ii} + W_{hi} h_{t-1} + b_{hi}\right) \tag{9}$$

$$f_t = \sigma\left(W_{if} x_t + b_{if} + W_{hf} h_{t-1} + b_{hf}\right) \tag{10}$$

$$g_t = \tanh\left(W_{ig} x_t + b_{ig} + W_{hg} h_{t-1} + b_{hg}\right) \tag{11}$$

$$o_t = \sigma\left(W_{io} x_t + b_{io} + W_{ho} h_{t-1} + b_{ho}\right) \tag{12}$$

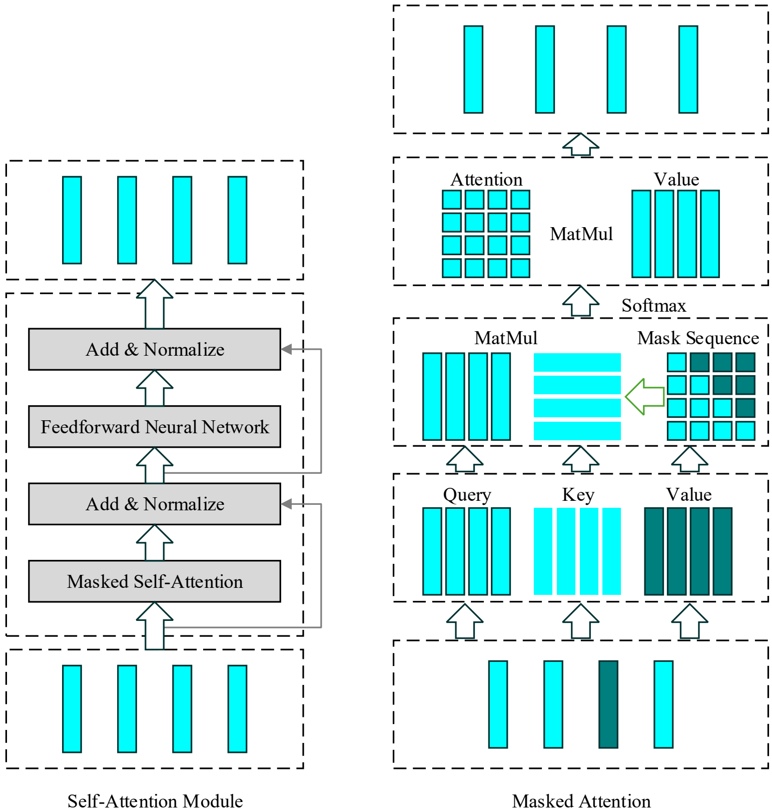
$$c_t = f_t \circ c_{t-1} + i_t \circ g_t \tag{13}$$

$$h_t = o_t \circ \tanh\left(c_t\right) \tag{14}$$

where h_t is the implicit unit at time t, c_t is the cell unit at time t, x_t is the input at time t, which is the t^{th} row of the input matrix X. The hidden unit state h_{t-1} from the previous time step is adopted to pass historical information. When the time step is 0, h_{t-1} in this layer is initialised to 0 for the hidden unit. W_{ii}, W_{hi}, W_{if}, W_{hf}, W_{ig}, W_{hg}, W_{io}, W_{ho} are weights between different layers, and b_{ii}, b_{hi}, b_{if}, b_{hf}, b_{ig}, b_{hg}, b_{io}, b_{ho} are biases between different layers. Additionally, i_t, f_t, g_t, o_t represent the input gate, forget gate, cell gate, and output gate, respectively. These gates are controlled by the Sigmoid function σ, and $\circ$ is the Hadamard product.

Through these calculations, the final result X with the same dimension as the input is obtained, where each vector at every time step contains historical information from the beginning of the sequence to the present time step. This information is passed to the subsequent Transformer encoding layer to enable more accurate online education effect evaluation.

Figure 2 Self-attention module in transformer (see online version for colours)



3.5 Long-term dependency modelling of user historical evaluation behaviour based on transformer

Users' evaluation behaviours (such as ratings, comments, and interaction frequency) on online education platforms are significantly influenced by historical behaviour sequences, but conventional RNN and GRU architectures exhibit fundamental limitations in modelling long-range temporal dependencies across sequential time steps. By introducing the self-attention mechanism (Kumar and Solanki, 2023), transformer overcomes the limitations of traditional RNN, improves the ability to model long-term dependencies, and significantly enhances performance in different sequence processing tasks. The self-attention (SAM) module in transformer is shown in Figure 2. The basis of SAM is assigning different attention weights to each element in the input sequence, as shown in equation (15).

$$Attention(Q, K, V) = softmax\left(\frac{QK^{\mathrm{T}}}{\sqrt{d}}\right)V \tag{15}$$

where Q, K, and V stand for queries, keys, and values, individually. First, the dot product of Q and K is calculated QK^{T} and then the softmax function is applied to obtain an attention weight matrix. Each entry in this matrix represents the similarity between corresponding Q and K. Subsequently, these similarities are used as weights to calculate the weighted sum of values in V. To prevent the gradient from becoming too small when the input dot product is too large in the softmax function, a scaling factor $\sqrt{d}$ is introduced, which helps stabilise the training process.

When modelling historical evaluation behaviour sequences using the self-attention module, to ensure that future events do not affect the current stay representation, causality needs to be reinforced. This can be achieved by combining LSTM with the self-attention mechanism, but a more direct method is to add negative infinity values at the corresponding positions, so that after the softmax operation, these positions approach 0, thereby strengthening the constraint of causality.

Z_j collects the representation of all sequence-related activity stay records obtained through self-attention and FPN transformations. Based on the transformer architecture, stacking multiple self-attention blocks, each module comprises a self-attention mechanism for contextual relationship modelling, followed by a position-wise FPN for nonlinear transformation, can further improve performance. To optimise model training, stability and acceleration measures are taken between layers, performing the following operations, where Sublayer(x) represents the self-attention or feed-forward network layer, and LayerNorm(x) represents level normalisation.

$$f(x) = \mathrm{LayerNorm}(x + \mathrm{Dropout}(\mathrm{Sublayer}(x))) \tag{16}$$

3.6 Real-time effect prediction and evaluation in online education

To assess the real-time efficacy of online learning, the proposed approach incorporates the unique evaluation identifier b_{c_i} of user c_i. Since user information is static during training, it is introduced after time modelling and is not directly input into the RNN. Instead, after being processed by the MAM mechanism, it is linearly combined with the output of the fully linked level, as shown below.

$$O^{c_i} = W^o A^{c_i} + b_o \tag{17}$$

$$y^{c_i} = softmax\left(O^{c_i} + W^u b_{u_i}\right) \tag{18}$$

There are two trainable weight matrices W^o and W^u. U is the total amount of online education users, L is the total amount of positions, b_o is the bias parameter of the fully linked level. To train the LSTM-transformer model, the cross-entropy function is adopted as the target function.

$$\mathcal{J} = -\sum_{u_i \in U} \sum_{i=1}^{L} l_i^{u_i} \log\left(y_i^{u_i}\right) + \lambda \|\Theta\|_2 \tag{19}$$

where $l_i^{u_i}$ is the true value of user u_i at each position, λ is the L2 regularisation parameter, and regularisation involves all learnable parameters Θ. The LSTM-Transformer model is trained using the cross-entropy function and L2 regularisation (with parameter λ). During training, the Adam optimiser and backpropagation through time (BPTT) are used to update the model parameters, aiming to minimise the objective function.

4 LSTM-transformer model parameter optimisation based on Bayesian optimisation algorithm

The online education effect evaluation model based on LSTM-Transformer mentioned above can enhance the accuracy of evaluation to a certain extent. Whereas, this hybrid structure still has a series of problems in practical applications, involving training efficiency, algorithm complexity, etc. Therefore, this paper proposes a Bayesian optimisation algorithm (RFBO) based on random forest (Speiser et al., 2019), which adaptively optimises the hyperparameters of the LSTM-transformer combined model, breaking the previous situation where there was no hyperparameter optimisation in previous research. Using the random forest algorithm for feature selection on the dataset to generate a new training set, then combining it with Bayesian optimisation (SMBO) (Victoria and Maragatham, 2021) to train the LSTM model. Furthermore, the test set is used as the input of the LSTM-Transformer model trained by Bayesian optimisation, to verify the prediction results and output the final results.

The proposed method first designs the RFBO algorithm to train the LSTM-transformer model as a local user model. After the model completes hyperparameter optimisation, the best hyperparameters are selected. The local user model then trains the fused model with the best hyperparameters. The following describes the RFBO algorithm used. First, the SMBO algorithm in the RFBO framework is introduced. The SMBO algorithm has two important parts: one is the surrogate model, and the other is the optimisation strategy. The surrogate model is used to model the objective function. The optimisation strategy determines the position of the next sample point, that is, where the function value $f(x)$ should be observed next at input x.

It is usually implemented through an acquisition function: the acquisition function is typically a function derived from the surrogate model, whose input is any value in the feasible set A, and the output value measures how worthwhile each input x is to be observed. The parameters in the Gaussian process regression model (mainly the mean function and the parameters in the kernel function) are automatically learned from the observed data. The method of learning is the maximum a posteriori estimation (MAP), which selects the most likely parameter values given the observed values, as shown in formula (20). Among them, η is the parameter set, and $P(\eta | F(x_{1:t}) = f(x_{1:t}))$ is the probability distribution of the parameters after all observed values are obtained. Converted using Bayes' formula, as shown in equation (21).

$$\hat{\eta} = \arg\max_{\eta} P\left(\eta \middle| F\left(x_{1:t}\right) = f\left(x_{1:t}\right)\right) \tag{20}$$

$$P\left(\eta \middle| F\left(x_{1:t}\right) = f\left(x_{1:t}\right)\right) = \frac{P\left(F\left(x_{1:t}\right) = f\left(x_{1:t}\right) \mid \eta\right) P(\eta)}{P\left(F\left(x_{1:t}\right) = f\left(x_{1:t}\right)\right)} \tag{21}$$

SMBO performs well in handling continuous or numerical parameters, but is not suitable for discrete parameters or parameters with conditional relationships in machine learning. To this end, this paper proposes the RFBO algorithm, aiming to solve the problem that traditional Gaussian process optimisation cannot be directly applied to discrete parameters, and to provide a parameter optimisation method for the LSTM-transformer model.

First, the random forest is modelled, assuming that there are some initial sample points $\{(x_1, f(x_1)), (x_2, f(x_2)), \ldots, (x_n, f(x_n))\}$. Then, the random forest model is established based on these points to fit the function f, and the process is similar to building a multidimensional distribution model using n points. Since the random forest can handle discrete variables, it naturally applies to the case of discrete parameters. For conditional constraints, by setting constraints in the parameter space, impossible situations can be avoided from being sampled by the model. When each tree splits, the feature ratio is randomly selected as 5/6, the minimum number of data required for the leaf node is 10, and the number of trees is also 10.

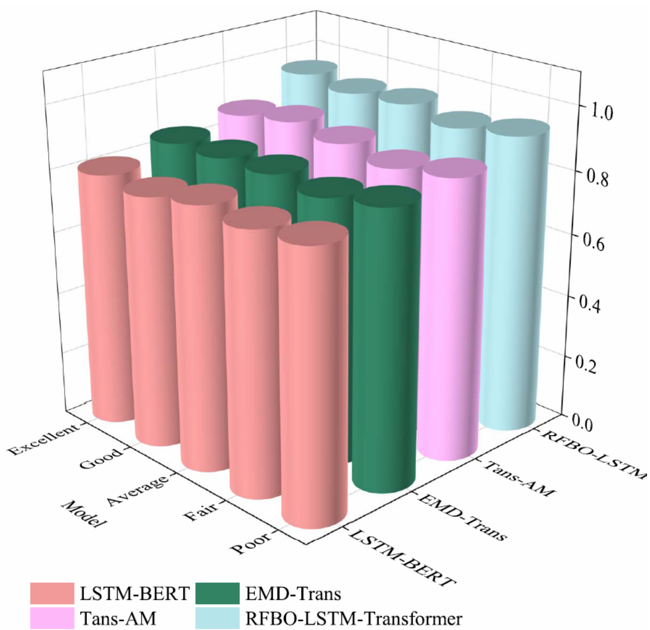
Next, calculate the mean and variance: each tree provides a prediction result during the Gaussian regression process. In the random forest, when a new point x is added, it does not form a new multidimensional normal distribution, but instead infers its characteristics through the prediction results of each tree. For the new point x, each tree will give a prediction value, and the average of these prediction values can be regarded as the predicted mean of the point, and the standard deviation of the prediction results is the standard deviation. Finally, the iteration point is selected, and the point that maximises $f(x)$ is selected as the optimal parameter for the LSTM-transformer model.

The time complexity of LSTM is $O(T{\cdot}d^2)$, where T is the sequence length and d is the hidden layer dimension. The recursive structure of LSTM makes parallelisation difficult, resulting in low efficiency during training on long sequences. The time complexity of the transformer component is $O(T^2{\cdot}d)$, with multi-head attention further amplifying computational demands. Although transformers can be optimised using scaled dot-product attention, long sequences still require reliance on chunking or sparse attention. When using a sequential structure (e.g., LSTM followed by transformer), the total time complexity is the sum of both. When employing a parallel structure, additional computational overhead for feature fusion must be accounted for.

5 Experimental results and analyses

The dataset used in this paper comes from China University MOOC, which contains 35,874 pieces of students' online evaluation data. After cleaning and removing dirty data, a total of 18,627 evaluation text data were obtained. This paper is based on a platform equipped with an NVIDIA GeForce RTX 3090 GPU. The experiment uses Python as the programming environment. When building and training the model, the deep learning framework TensorFlow and the famous machine learning library Scikit-learn are mainly used. The optimiser uses Adam, the studying rate is set to 0.001, the activation function selects ReLU, Dropout is set to 0.2, the weights of LSTM and transformer are both set to 0.5, and the amount of multi-head attentions is set to 4.

Figure 3 Accuracy of assessment of different educational outcomes (see online version for colours)



The students' online education evaluation results are divided into five categories: poor, bad, average, good, and excellent. The prediction accuracy of RFBO-LSTM-transformer model and LSTM-BERT (Jiao, 2024), EMD-Trans (Venkateshwarlu et al., 2024), Tans-AM (Zhang, 2025) for different evaluation results is shown in Figure 3. The average accuracy of LSTM-BERT, EMD-Trans, Tans-AM, and RFBO-LSTM-transformer reached 81.42%, 84.75%, 87.68%, and 93.66%, respectively. Compared with LSTM-BERT, EMD-Trans, and Tans-AM, RFBO-LSTM-transformer improved by 12.24%, 8.91%, and 5.98%, respectively. Although LSTM-BERT uses LSTM to explore the temporal features of evaluation texts, it does not further extract the dependency relationship between evaluation texts and users' learning behaviours. EMD-Trans performs multi-dimensional feature extraction on the decomposed online education evaluation indicators through transformer, further improving the evaluation accuracy compared to LSTM-BERT, but it does not optimise the model parameters, so the evaluation accuracy is lower than that of RFBO-LSTM-transformer. Tans-AM uses transformer and attention mechanism to achieve synchronous feature extraction of evaluation sequence information in two dimensions of course and time, but it does not optimise the model parameters, so the evaluation accuracy is lower than that of RFBO-LSTM-transformer.

The R^2, MAE, RMSE, MAPE evaluation indicators of RFBO-LSTM-Transformer compared with the main baseline methods are implied in Table 1. From the above table analysis, it can be seen that RFBO-LSTM-Transformer achieved the best evaluation prediction effect. Compared with LSTM-BERT, EMD-Trans, and Tans-AM models, it improved by 0.73%, 1.08%, and 1.3% respectively in R^2. Moreover, it achieved the lowest MAE, indicating that the model with Bayesian algorithm obtained smaller errors. Similarly, the model also achieved the best RMSE and MAPE, indicating the reliability and robustness of the model.

Comparing the R^2 of four models, LSTM, transformer, LSTM-transformer, and RFBO-LSTM-transformer, based on the final simulation results, as shown in Figure 4. Figure 4(a), Figure 4(b), Figure 4(c), and Figure 4(d) show the R^2 simulation results of LSTM, transformer, LSTM-transformer, and RFBO-LSTM-transformer, respectively. The maximum R^2 of LSTM on the training set is 0.9806, and on the test set is 0.9834. The maximum R^2 of transformer on the training set is 0.963, and on the test set is 0.9856. The maximum R^2 of LSTM-transformer on the training set is 0.9638, and on the test set is 0.9891. The maximum R^2 of RFBO-LSTM-transformer on the training set is 0.9651, and on the test set is 0.9664. It can be seen that RFBO-LSTM-transformer has the best prediction effect. RFBO-LSTM-transformer not only mines the temporal features of students' historical evaluation texts, but also further optimises the parameters of the evaluation model through RFBO, enhancing the accuracy of real-time effect evaluation in online education.

Figure 4 Comparison of evaluation errors between different models, (a) LSTM, (b) transformer, (c) LSTM-transformer, (d) RFBO-LSTM-transformer (see online version for colours)

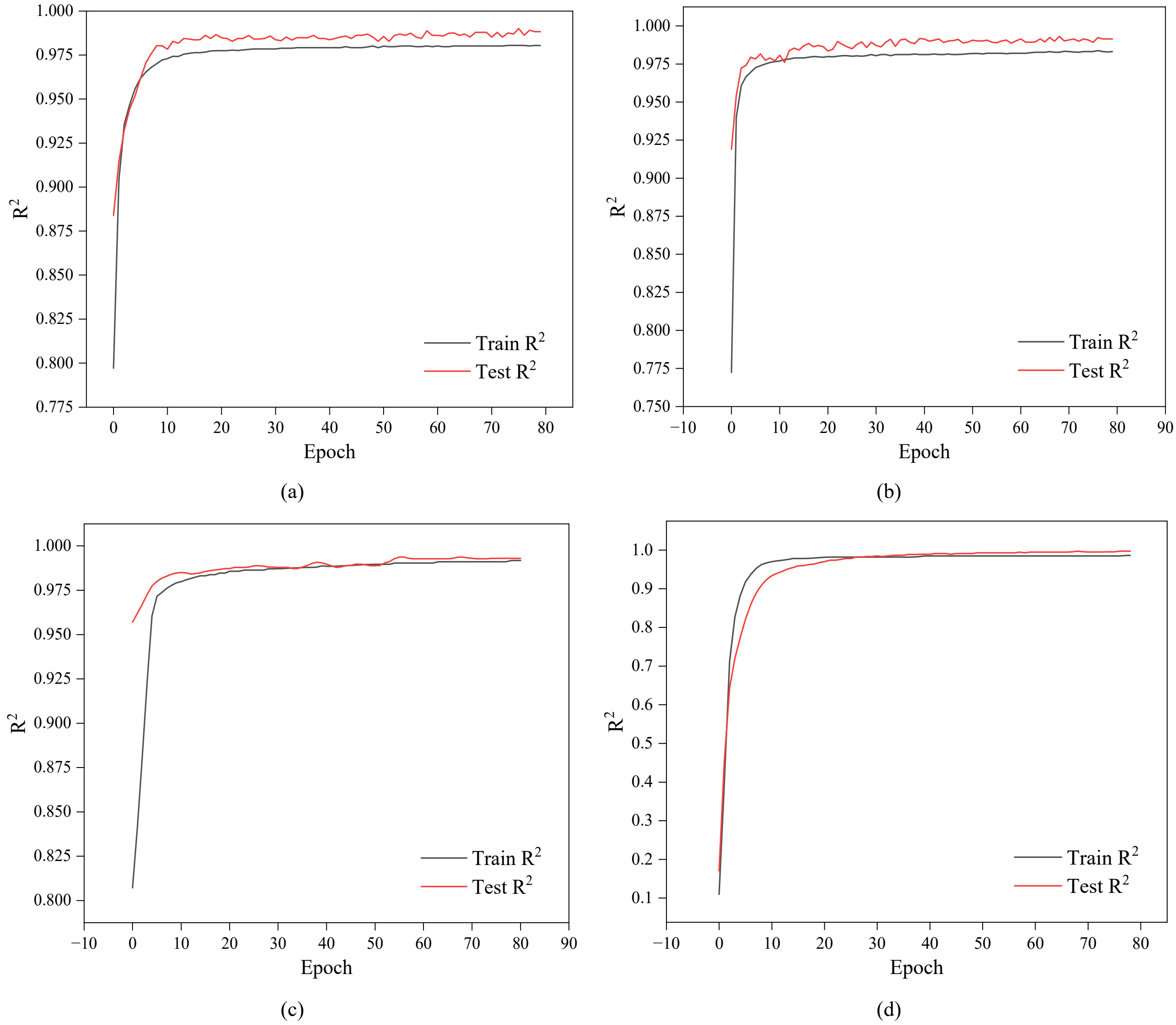


Table 1 Performance comparison of real-time effectiveness assessment of different online education methods

Model	R^2	*MAE*	*RMSE*	*MAPE*
LSTM-BERT	0.9834	0.0054	0.0069	0.0013
EMD-Trans	0.9856	0.0033	0.0061	0.0007
Tans-AM	0.9891	0.0024	0.0055	0.0002
RFBO-LSTM-transformer	0.9964	0.0018	0.0032	0.00008

6 Conclusions

Focusing on the issues of insufficient capture of spatiotemporal locality and high model complexity in current online education effect evaluation, this paper proposes an online education real-time effect evaluation model in light of the LSTM-Transformer model. First, the historical evaluation sequence of users is modelled, and the historical sub-sequences are connected into an overall trajectory, which is then sent to the spatiotemporal embedding module to obtain information about time and spatial relationships. The overall evaluation trajectory is connected with the user embedding to form a comprehensive input. Next, the transformer model is introduced to generate a series of learning behaviour representations, which contain important information at each time point and can capture the long-range dependencies between different user evaluation behaviours. This is to better understand the patterns and trends in the historical user evaluation behaviour sub-sequences. Finally, the RFBO algorithm is designed. This algorithm trains the LSTM-transformer model as a local user model, and after the model completes hyperparameter optimisation, the best hyperparameters are selected. The local user model then trains the fused model with the best hyperparameters, thereby improving the prediction accuracy of online education effect evaluation. Experimental outcome indicates that the coefficient of determination of the proposed model is 0.9964, which is better than the comparison models, indicating that the proposed model can be well applied to online education real-time effect evaluation.

This paper suggests a parameter optimisation approach for the LSTM-Transformer model based on the RFBO algorithm, and verifies its effectiveness in the experimental environment. However, there may still be better feature processing methods and more model fusion methods. For example, hyperparameter tuning significantly improves prediction accuracy, but also brings a greater computational burden, affecting the training efficiency of the model. Therefore, one of the future research directions is how to integrate more feature information to improve the accuracy of evaluation prediction, while paying attention to the training efficiency of the model, further optimising the hyperparameter tuning algorithm. In addition, the generalisation of the model on different datasets is also a problem that needs further study.

Declarations

All authors declare that they have no conflicts of interest.

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