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PAPER

# Optimization of Online Learning Resource Adaptation in Higher Education through Neural Network Approaches

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**ABSTRACT**

With the advent of the digital era, the quantity and variety of online higher education learning resources have expanded rapidly. The efficient adaptation of suitable resources to meet the needs of learners with specific requirements has become crucial for improving learning outcomes. Although current online learning resource recommendation systems have made some progress in matching resources, they still face challenges related to the inadequate integration of resource features and a superficial understanding of learners' needs. These challenges hinder the achievement of personalized and precise matching, affecting learners' study efficiency and the effective utilization of educational resources. This study first analyzes the importance of adapting online higher education learning resources and the limitations of existing research. Subsequently, a novel neural network optimization strategy is proposed. The research comprises two main parts. Firstly, the self-attention-convolutional neural network (SA-CNN) model is employed for the deep integration of the content features of online learning resources. This aims to enhance the comprehensiveness of resource descriptions. Secondly, a deep-metric attention model is introduced to accurately model and adapt to learners' needs. This approach not only optimizes the feature representation of learning resources but also enhances the sensitivity and accuracy of the recommendation system towards learners' requirements. This study is of significant importance for improving the performance of higher education online learning resource recommendation systems. It also provides new insights into the construction of personalized learning paths and ensuring the balanced allocation of educational resources.

**KEYWORDS**

online learning resources, resource adaptation, neural network optimization, simulated annealing-convolutional neural network model, deep metric attention model, personalized recommendation

## 1 INTRODUCTION

As the rapid development of information technology converges with innovations in educational paradigms, online learning in higher education has emerged as a

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crucial component of the contemporary educational system [1–3]. The diversity and richness of online learning resources provide learners with unprecedented convenience and choices, yet they also introduce challenges related to resource overload and imprecise matching. The effective alignment of appropriate learning resources with learners who have specific needs has been recognized as a key challenge in improving the efficiency and effectiveness of online learning [4–7].

The investigation into this issue is of profound significance. By accurately adapting learning resources, not only can learners' interest and efficiency be improved, but the formation of personalized learning paths can also be facilitated, thereby enhancing the overall teaching quality of higher education [8–10]. Furthermore, research focused on demand-oriented resource adaptation holds significant value for optimizing the allocation of educational resources and advancing educational equity [11–13].

However, current research methodologies have limitations in identifying and integrating the content features of online learning resources, struggling to comprehensively capture the multidimensional characteristics of these resources. Moreover, there is a lack of sufficient granularity in accurately understanding and adapting to learners' needs [14–16]. These deficiencies limit the personalized service capabilities of online learning resource recommendation systems, preventing them from fully meeting the specific needs of diverse learners.

This study aims to enhance the adaptation of online higher education learning resources through advanced neural network optimization techniques. In the first part of the study, the self-attention-convolutional neural network (SA-CNN) model is utilized to achieve deep fusion of content features from online learning resources, enhancing the comprehensiveness and distinctiveness of feature representation. In the second part, a deep metric attention model is utilized to optimize the adaptation process between learning resources and learners' needs, specifically enhancing the accuracy and flexibility of the model in personalized recommendations. Overall, the thesis not only explores the application of neural networks in the field of educational resource adaptation theoretically but also demonstrates the potential of enhancing adaptation precision through technological optimization in practice. This offers significant research value and application prospects for the development of online teaching resource allocation and recommendation systems in higher education.

## 2 INTEGRATION OF CONTENT FEATURES IN ONLINE HIGHER EDUCATION LEARNING RESOURCES

With the advancement of internet technology, higher education resources have been digitized and networked. However, the quality and applicability of these resources vary widely. Furthermore, students have diverse educational backgrounds, knowledge bases, and learning styles. Through the study of integrating content features of higher education resources, these resources can be more effectively consolidated and optimized to align more closely with the actual needs of learners, thereby enhancing learning efficiency. Network optimization can offer comprehensive data analysis on the efficiency of learning resource utilization, assisting educational administrators and teachers in making more scientifically informed instructional decisions. This can also contribute to the enhancement of course design and teaching methodologies. To this end, a method for integrating the content features of online higher education learning resources using the SA-CNN model is proposed, with the method's architecture illustrated in Figure 1.

In the initial phase of the SA-CNN model, offline training is required using historical learning behavior data to simulate the features of learning resources and determine model parameters, as the weights of parameters are not fixed. Subsequently, the model enhances its capability to mine the content features of educational resources through iteration and adjustment. In practical applications, the model receives real-time learning behavior data and applies the offline-trained model to predict the content features of educational resources. This process helps in obtaining an assessment of the current learning resource's adaptability. If the assessment result indicates that the resource adaptability is below a certain threshold, adjustments or feedback can be promptly provided to ensure the effectiveness and personalized adaptation of the learning resources. In summary, this process involves inputting historical and real-time data from online higher education learning resources into the trained SA-CNN model. This model is used for predicting and optimizing the adaptability of educational resources and content features to learners' needs, ensuring personalized matching of teaching resources, and continuous improvement in teaching quality.

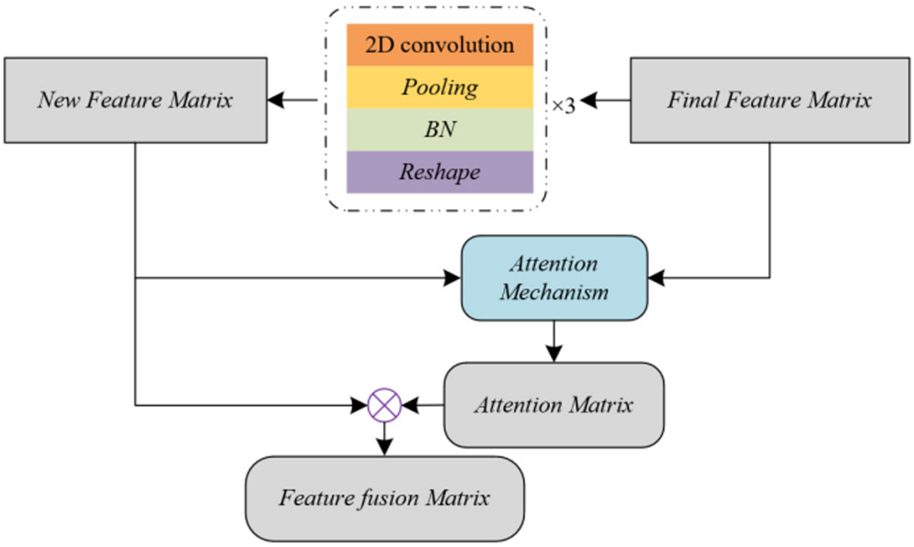



**Fig. 1.** Content feature integration structure of online higher education learning resources

In the construction of the model for integrating content features of online higher education learning resources, a data collection and preprocessing module is initially established. This refers to the collection and initial processing of learning behavior data in a higher education setting, ensuring data quality, and preparing for feature selection. Subsequently, an incremental feature selection module is established to identify the most relevant features for learning outcomes from a large volume of educational data. This data may encompass students' interaction data, grades, feedback, and more. This process improves the model's prediction accuracy and efficiency. Following this, the SA-CNN feature fusion module is tasked with effectively combining selected features using deep learning techniques to capture the complex nonlinear relationships between learning resources and student performance. Finally, a monitoring module is established to predict the adaptability of learning resources, providing teachers and educational workers with guidance and feedback on resource enhancement.

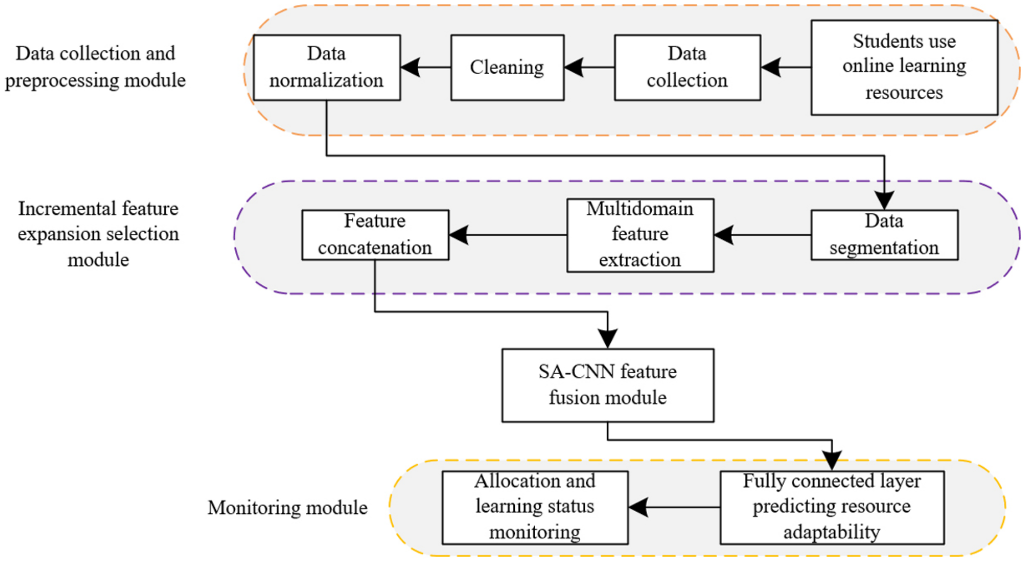



**Fig. 2.** Content feature integration workflow of online higher education learning resources

The specific steps of the model for integrating content features in online higher education learning resources are as follows, with the detailed model workflow depicted in Figure 2.

**i)** Data from various sources, including clickstreams, grades, and forum interactions, is collected to represent students' online learning behaviors. The data undergoes denoising and normalization processes to generate new time-series signals, ensuring the quality and consistency of the data.

**ii)** The preprocessed multidimensional time-series signals undergo incremental feature selection techniques to identify temporal features that reflect students' learning progress and the effectiveness of resource usage. This process yields multidimensional features containing time information and the status of learning resource usage.

**iii)** The multidimensional features obtained are input into the SA-CNN, which utilizes the network to fuse features across different time scales and determine the relevance weights between different learning behavior features. This step involves extracting comprehensive features that fully reflect the association between the content of learning resources and students' learning outcomes.

**iv)** A deep, fully connected regression or classification layer is designed to map the fused features to the applicability of learning resources according to actual application requirements. This facilitates the accurate assessment of personalized matching and the effectiveness of educational resources.

In the online learning environment of higher education, digital resources include, but are not limited to, video lectures, interactive simulations, reading materials, and online quizzes. To enhance the adaptability and effectiveness of these learning resources, a similar multivariate time-series analysis method is adopted to predict and evaluate the effectiveness and adaptability of learning resources. This method involves deeply analyzing and integrating the content features of these resources with students' learning behaviors and outcomes.

Initially, a systematic collection of various data generated by students using online learning resources is undertaken, such as video-watching duration, responses to interactive questions, and participation in discussion boards. The data is cleansed and normalized to reduce noise and eliminate the influence of dimensions, ensuring the accuracy of subsequent analyses. In the time-frequency domain, incremental feature selection technology is combined to select features most related to learning outcomes, such as critical moments of learning behavior and the intensity of resource interaction. These are represented as a two-dimensional matrix $A_{v*I\_C}$, where '$v$' represents the variable and $I\_C$ denotes the data length.

A CNN model is designed to process extracted multidimensional features using multiple convolutional layers and nonlinear activation functions, such as ReLU. Convolutional layers are capable of capturing local dependencies and patterns, such as the specific interaction patterns of students with a particular learning resource. Let the size of the convolution kernel be denoted by $g$, the convolution kernel for the $k$-th variable by $n_k$, and the bias term by $y$. The complete convolution operation expression is given by:

$$z_k^g = n_k \cdot a_u^{g-1} + y \tag{1}$$

Assuming the stride of the sliding is denoted by $t$, the size of zero-padding by $o$, and the kernel size by $g$, the output length after the convolution operation is expressed as $(1-g+2o)/t+1$. The vector after the operation is:

$$z_k = [z_k^1, z_k^2, \cdots, z_k^{(l-g+2o)/t+1}]^T \tag{2}$$

After the convolution operation, the feature maps undergo batch normalization to expedite the model learning process and introduce nonlinearity through an activation function to enhance the model's expressive capacity. Assuming the input batch data is denoted by $Y = \{y1, y3, \ldots, y_V\}$, the mean of data $Y$ by $\psi_Y$, and the deviation of data $Y$ by $\omega_Y$, the calculation is as follows:

$$\psi_Y = \frac{1}{V}\sum_{u=1}^{V} y_u \tag{3}$$

$$\omega_Y = \frac{1}{V}\sum_{u=1}^{V} y_u \tag{4}$$

$$\hat{y}_u = \frac{y_u - \psi_Y}{\sqrt{\omega_Y^2 + \gamma}} \tag{5}$$

Assuming the parameters to be learned are denoted by $\varepsilon$ and $\alpha$, the output $YV_{\varepsilon,\alpha}(y_u)$ is:

$$YV_{\varepsilon,\alpha}(y_u) = \varepsilon \hat{y}_u + \alpha \tag{6}$$

Assuming the activation function is represented by $d(\cdot)$, the following expression involves additional convolution and activation operations:

$$x_k^g = d(YV(n_k^S a_k^g + y)) \tag{7}$$

Through the implementation of a max-pooling layer, the number of parameters and computational complexity are reduced while retaining the most important feature information. Subsequently, a fully connected layer integrates all features to construct a comprehensive feature representation, providing global information to enhance the adaptability of learning resources. Letting the sliding stride equal $j$, the output computation formula for the max-pooling operation is provided as follows:

$$l_k = [l_k^1, l_k^2, l_k^3, \ldots, l_k^{(m-k+2o)/t+1}]^S \tag{8}$$

were,

$$l_k^u = MAX(x_k^{(u-1)t}, x_k^{(u-1)t+1}, \ldots, x_k^{(u-1)t+j-1}) \tag{9}$$

Feature maps within the connection layer are synthesized into a single feature map, where local and abstract features are fused to obtain a 2D matrix, represented by $L_{O\_C^*v}$. The model incorporates a self-attention mechanism, enabling the distribution of different attention weights among various features, thereby highlighting the most critical features. This mechanism automatically identifies the content features of resources that have the most significant impact on learning outcomes. Specifically, for inputs $A$ and $L$, the specific output computation formula is provided as:

$$AT(A, L) = \mathrm{softmax}\left(\frac{AL}{\sqrt{f_L}}\right) \tag{10}$$

Finally, the output layer maps the feature matrix to the adaptability assessment of learning resources, such as learning performance, satisfaction surveys, and other indicators. This step represents the objective of the entire model training process, which is to optimize model parameters to maximize the accuracy of predictions. Assuming the attention matrix is represented by $X_{v^*A\_C}$, the formula for the computed feature matrix $D$ is given as:

$$D = L_{O\_C^*v} \times X_{v^*A\_C} \tag{11}$$

## 3 DEMAND-ORIENTED ONLINE LEARNING RESOURCE ADAPTATION FOR HIGHER EDUCATION

In the demand-oriented online learning resource adaptation model for higher education proposed in this study, the deep metric attention model plays a pivotal role. Initially, convolutional layers are used to map raw data associated with learners and learning resources into a high-dimensional feature space, capturing complex data patterns. Subsequently, through the application of the channel attention (CA) mechanism, the model can identify and enhance the feature channels that are more important to learners' needs, thereby achieving personalized resource adaptation. The model then delves deeper into the intricate relationship between learning resource content features and learner behavior through a series of feature extraction modules. These features are subsequently passed to a fully connected layer with 64 neurons, serving as an integration point for deep features and transforming them into effective learning resource recommendations. Finally, the classification results output by the SoftMax classifier are combined. Through the joint optimization of metric loss and classification loss, network parameters are refined to meet the diverse needs of learners. Figure 3 illustrates the architecture of the online learning resource adaptation model for higher education.

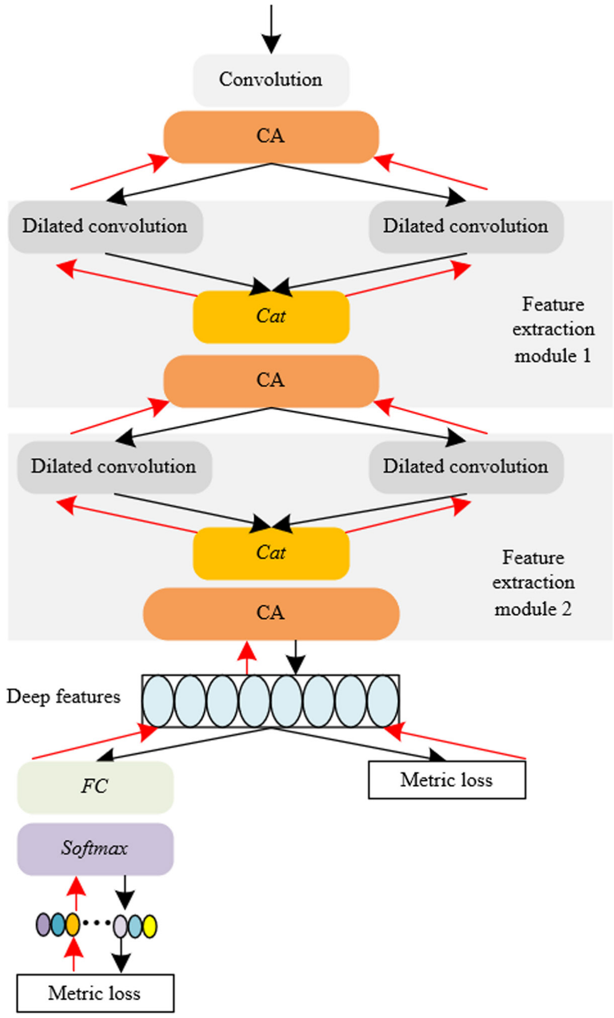



**Fig. 3.** Architecture of the online learning resource adaptation model for higher education

## 3.1 Dilated convolution

To enhance the model's capability to capture learners' needs and provide more precise learning resource recommendations, dilated convolution is introduced in the demand-oriented online learning resource adaptation model for higher education within this document. Dilated convolution, similar in core mechanism to standard convolution for feature extraction using convolution kernels, expands the receptive field by adjusting the dilation rate. This allows the model to perceive a broader range of input information without increasing the computational burden. This characteristic makes dilated convolution particularly suitable for learning resource adaptation scenarios. It enables the model to integrate more contextual information without losing local features, thereby enhancing its ability to understand the comprehensive needs of learners.

Let $c_k \in R^Z$, $u \in [1, V]$, and $a_{u:u+e} = [a_u, a_{u+1}, \ldots, a_{u+e}]$. The number of convolution output channels is denoted by $Z$, and the ReLU activation function is denoted by $\delta_{RE}$. The size of the receptive field is denoted by $e$, the dilation rate by $f$, the convolution kernel size by $J$, the convolution operation by $*$, and the convolution kernel's weights and bias by $Q^s$ and $y$, respectively, with the length of the input signal represented by $V$.

The following expression provides the dilated convolution process and its receptive field calculation:

$$\begin{cases} C_k = \delta_{RE}(Q^S * a_{u:u+e} + y) \\ e = (f-1)\times(j-1)+J \end{cases} \tag{12}$$

### 3.2 CA module

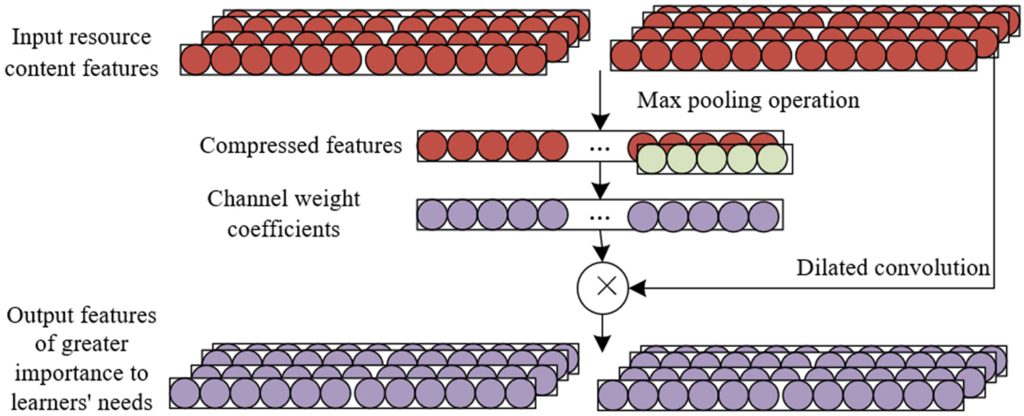



**Fig. 4.** Architecture of the CA module

In the demand-oriented online learning resource adaptation model for higher education, the CA module is designed to adjust the weighting of input features across different channels. This refinement aims to improve the model's sensitivity and responsiveness to learners' needs. Specifically, the model receives serialized feature inputs $U$ (with $Q$ representing the sequence length and $Z$ the number of channels) and, through a global average pooling operation, compresses them into a 1D channel descriptor $U^*$ to simplify the global information. To capture and utilize the dependencies between channels, $U^*$ is then processed with dilated convolution combined with a sigmoid activation function. This step captures a broader context by utilizing an expanded receptive field, while the implementation of dilated convolution guarantees an increased receptive field size without changing the feature dimensions. The generated weight coefficients $U'$ assign a learned weight to each channel, reflecting its importance to the current learner's needs. Finally, by performing element-wise multiplication of the weight coefficients with the original input features, the weighted feature output $P$ is obtained, thus achieving channel-level recalibration of the input features. Such a CA mechanism allows the model to better identify and respond to the relative importance of each channel under different learning contents and learners' needs. Figure 4 illustrates the architecture of the CA module.

Assuming the input data is denoted by $U$, the max pooling operation by $MAP$, the dilated convolution operation by $DCO$, and channel weighting by $\times$, the following operation process is then established:

$$P = DCO(MAP(U)) \times U \tag{13}$$

### 3.3 Feature extraction module

In the model, the feature extraction module is established to capture deep correlation features between learning resource content and learner behavior through multi-scale information processing while also focusing on the personalized needs of learners. This module utilizes two parallel dilated convolution layers. By employing different dilation rates, these layers explore features of the input signal at various scales. This approach allows the model to capture not only local information but also a broader range of contextual information without increasing computational complexity. By concatenating these multi-scale features, the model obtains a rich feature representation, which is further refined by introducing a CA mechanism. This mechanism, by learning the importance of each channel, weights the features, enabling the model to highlight features that are more relevant to learners' needs.

Assuming the input data to the feature extraction module is denoted by $P_{IN}$, the dilated convolutions are represented by $CO\_u1$ and $CO\_u2$, concatenation according to data dimensions by $TO.CA$, and the CA operation by $ZX\_u$. The following expression then describes the operation of the feature extraction module:

$$P_{OU} = ZX\_u(TO.CA[CO\_u1(P_{IN}), CN\_u2(P_{IN})]) \tag{14}$$

### 3.4 Network parameters and training optimization

In the demand-oriented online learning resource adaptation model for higher education, the design of network parameter settings and training optimization processes has thoroughly considered the need to enhance resource adaptation precision and prevent overfitting. The feature extraction part of the model utilizes dilated convolution layers to capture information across various scales. Batch normalization layers and ReLU activation functions are applied after each dilated convolution layer. These steps are taken to maintain numerical stability during the training process and prevent gradient vanishing or explosion, ensuring that the deep network can be effectively trained. After the fully connected layer, the dropout technique is applied to reduce the model's overfitting on the training data, thereby enhancing the model's generalization capability. These measures, working in concert, enable the model not only to deeply learn and differentiate the features of online learning resources but also to provide effective resource recommendations based on learners' personalized needs. Thus, they enhance the performance of online learning platforms by adapting resources and ensuring that learners receive educational content that aligns with their learning styles and needs.

## 4 EXPERIMENTAL RESULTS AND ANALYSIS

**Table 1.** Performance comparison of different online learning resource content feature fusion algorithms in higher education

| Method | Course Content Resources | | | Interactive Learning Tools | | | Supplementary Learning Materials | | |
|---|---|---|---|---|---|---|---|---|---|
| | MAE | RMSE | $R^2$ | MAE | RMSE | $R^2$ | MAE | RMSE | $R^2$ |
| VAE | 0.028 | 0.038 | 0.957 | 0.031 | 0.046 | 0.965 | 0.031 | 0.042 | 0.958 |
| Attention-RNN | 0.033 | 0.044 | 0.936 | 0.057 | 0.061 | 0.945 | 0.045 | 0.052 | 0.936 |
| Transformer | 0.021 | 0.032 | 0.968 | 0.026 | 0.032 | 0.978 | 0.016 | 0.027 | 0.987 |
| The proposed method | 0.013 | 0.012 | 0.989 | 0.02 | 0.022 | 0.986 | 0.015 | 0.02 | 0.98 |

**Table 2.** Performance comparison of various online learning resource adaptation algorithms in higher education

| Method | Average Precision | Recall | F1-Score | Standard Deviation |
|---|---|---|---|---|
| Kernel SVM | 43.25% | 71.23% | 42.13% | 0.0584 |
| CART | 68.59% | 72.69% | 72.26% | 0.0556 |
| XGBoost | 85.36% | 85.67% | 85.47% | 0.0147 |
| Naive Bayes | 85.32% | 88.44% | 88.32% | 0.0021 |
| Weighted KNN | 81.23% | 81.26% | 81.24% | 0.0215 |
| MLP | 88.69% | 91.58% | 88.36% | 0.0075 |
| K-Means | 87.56% | 91.24% | 92.14% | 0.0426 |
| Apriori | 91.23% | 92.23% | 92.36% | 0.0123 |
| DQN | 96.58% | 98.14% | 96.84% | 0.0032 |
| The proposed method | 97.23% | 96.87% | 97.58% | 0.0029 |

The experimental results in Table 1 demonstrate that the method proposed here exhibits exceptional performance in adapting course content resources, interactive learning tools, and supplementary learning materials. The proposed method demonstrates a mean absolute error (MAE) of 0.013, a root mean square error (RMSE) of 0.012, and an $R^2$ score of 0.989 for course content resources. It significantly outperforms the variational autoencoder (VAE), attention-enhanced recurrent neural network (Attention-RNN), and transformer models. In the feature fusion test for interactive learning tools, the proposed method achieves a MAE of 0.02 and a RMSE of 0.022, with an R-squared ($R^2$) score of 0.986, surpassing the other three comparative methods. Similarly, for supplementary learning materials, the proposed method also demonstrates outstanding performance, with a MAE of 0.015, an RMSE of 0.02, and an $R^2$ score of 0.98. These results highlight the method's adaptability and accuracy across various types of learning resources. Analysis of the aforementioned data leads to the conclusion that the method proposed in this document has a distinct advantage in integrating the content features of online learning resources in higher education. Compared to existing algorithms, the proposed method significantly enhances the accuracy of feature fusion. This improvement can be attributed to the SA-CNN model's profound understanding of resource content and its precise adaptation to learners' needs.

In the performance comparison of online learning resource adaptation algorithms for higher education (Table 2), the method proposed in this study demonstrated superior performance across average precision, recall, and F1-score metrics. It achieved an average precision of 97.23%, recall of 96.87%, and an F1-score of 97.58%, with a very low standard deviation of 0.0029. This indicates the algorithm's stability and reliability. Compared to other commonly used algorithms, such as kernel support vector machine (SVM), classification and regression tree (CART), extreme gradient boosting (XGBoost), naive bayes, weighted K-nearest neighbor (KNN), multilayer perceptron (MLP), K-means, Apriori, and Deep Q-Network (DQN), it is evident that the proposed method improves upon all key metrics. Particularly when compared to the second-highest performer, DQN, the proposed method shows a slight increase in average precision and F1-score and demonstrates higher stability in terms of standard deviation. These results fully validate the effectiveness of the deep metric attention model in personalizing the adaptation of online learning resources in higher education. The method proposed, utilizing deep learning techniques, accurately models the intricate relationships between learning resources and learners' needs, thereby achieving more precise recommendations. In such a complex and variable data environment, the method maintains a very low standard deviation, indicating that the algorithm is not only accurate but also robust.

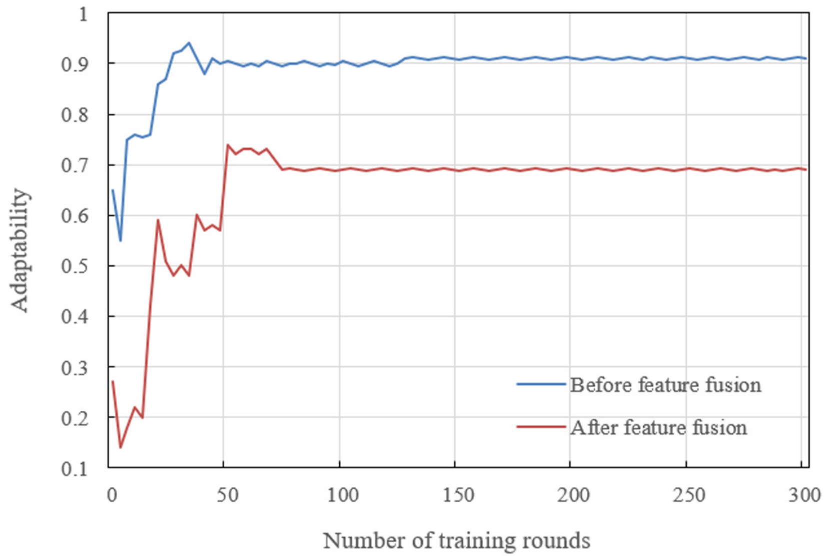
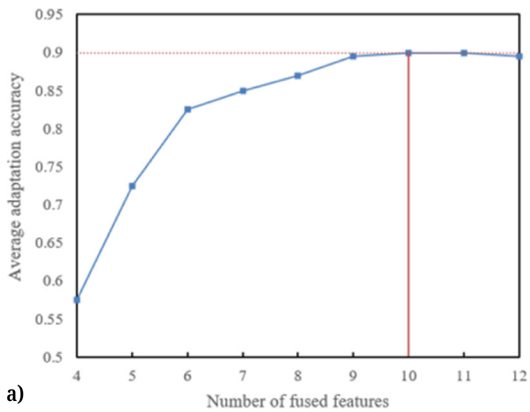



**Fig. 5.** Convergence comparison of online learning resource adaptation algorithms in higher education before and after feature fusion

According to Figure 5, the introduction of the SA-CNN model has significantly improved the feature representation of online learning resources in higher education. Empirical evidence demonstrates that this model rapidly enhances the adaptability between learning resources and learners' needs during the initial iterations. Despite significant fluctuations in adaptability within the first 50 iterations, adaptability tends to stabilize with an increase in the number of iterations, especially after reaching the 130th iteration, indicating the onset of model convergence. Furthermore, compared to the model before feature fusion, the SA-CNN model not only accelerates the convergence speed of the adaptation process but also achieves approximately a 32% improvement in the final convergence level. This significant finding confirms the effectiveness of combining content features to improve adaptability. The analysis results reveal that the model constructed in this study demonstrates remarkable effectiveness in the adaptation process of online learning resources in higher education. By deeply integrating the content features of learning resources, the SA-CNN model offers more precise personalized recommendations to learners, addressing their learning needs. This deep fusion approach not only enhances the distinctiveness of features but also, through the use of a deep metric attention model, further optimizes the adaptation process, ensuring the efficiency and flexibility of the recommendation system in personalized educational resource adaptation.

Further experimental analysis was conducted to assess the impact of the number of fused features on the model's adaptation accuracy, with the results clearly displayed in Figure 6. The experimental data indicate that as the number of fused features increases from a few to many, the model's average adaptation accuracy shows an initial increase followed by a subsequent decrease. As the number of features increases to ten, the system's adaptation accuracy gradually improves. This indicates that feature fusion within a specific range effectively enhances the model's adaptation capability. This implies that feature fusion, up to a certain extent, can effectively increase the alignment between learning resources and learners' needs, thereby enhancing the overall performance of the recommendation system. When the number of fused features exceeds ten, the adaptation accuracy starts to decline. This decline may be attributed to information redundancy or model overfitting resulting from excessive feature fusion. Therefore, the model needs to find an optimal balance between the quantity and quality of feature fusion to ensure the quality and efficiency of the final recommendations.



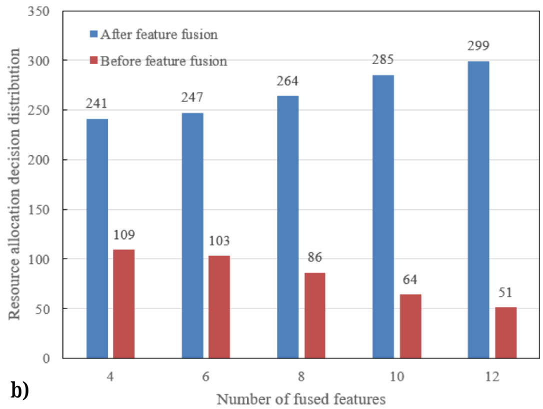




**Fig. 6.** Impact of the number of fused features on the performance of online learning resource adaptation algorithms in higher education

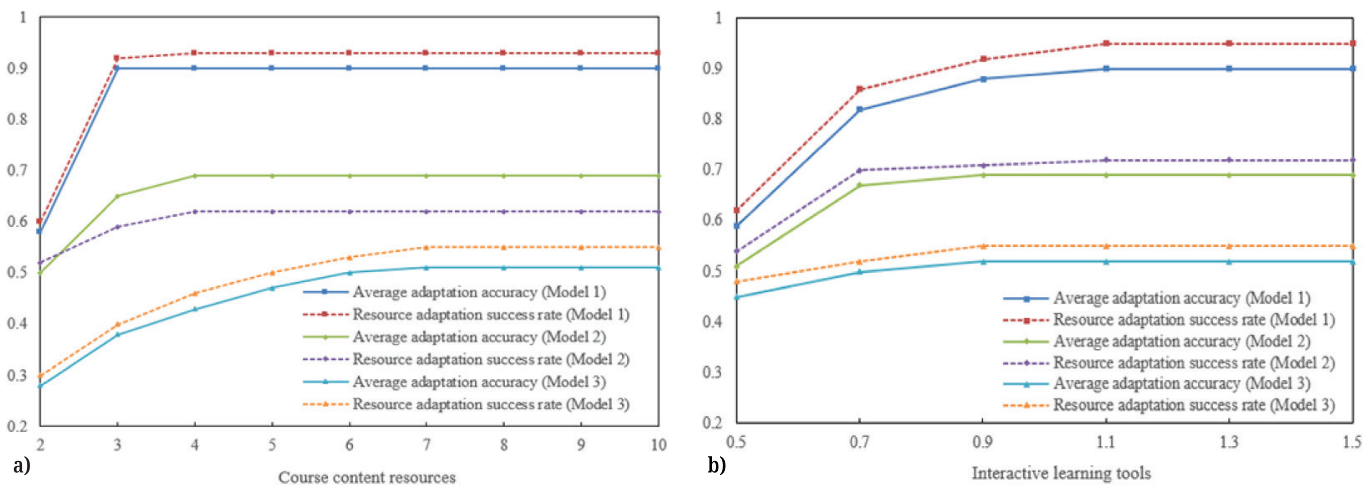
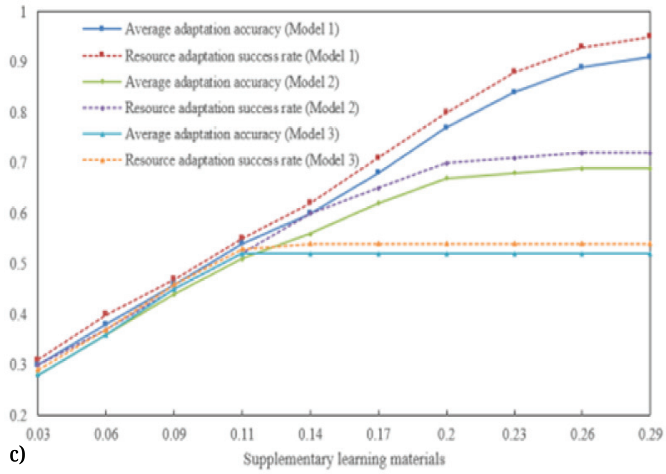



**Fig. 7.** *(Continued)*




c)

**Fig. 7.** Impact of the capacity of different resource types on the success rate of resource adaptation and the average adaptation accuracy

As demonstrated in Figure 7, the impact of varying resource type capacities on resource adaptation is showcased. After comparing the performance of three different model configurations, it is observed that the model proposed in this study (Model 1) demonstrates a clear upward trend in both adaptation success rate and average adaptation accuracy when managing increased volumes of course content resources, interactive learning tools, and supplementary learning resources. Specifically, compared to Model 2 (which lacks resource content feature extraction), the proposed model shows a 32% improvement in average adaptation accuracy. In comparison to Model 3 (which excludes the feature extraction module designed to capture the deep correlation between content features and learner behavior), there is a 75% improvement. In terms of resource adaptation success rate, the proposed model outperforms Models 2 and 3 by 1.34 times and 1.75 times, respectively. These experimental results indicate that the SA-CNN model and deep metric attention model proposed in this document exhibit significant advantages in adapting various types of online learning resources. Especially when the resource capacity is abundant, the proposed model can handle a greater number of adaptation tasks, both in terms of quantity and quality. This highlights the significance and effectiveness of deeply fusing learning resource content features and personalized recommendations in adapting online resources in higher education.

## 5 CONCLUSION

The primary research objective of this study was to improve the effectiveness of adaptation between online learning resources and learners' needs in higher education by utilizing advanced neural network models, specifically the SA-CNN and the deep metric attention model. Through the SA-CNN model, a successful deep fusion of online learning resource content features was achieved, enhancing the comprehensiveness and distinctiveness of feature representation. This augmentation increased the representational capacity of resource features during the adaptation process. The introduction of the deep metric attention model allowed for targeted optimization of the adaptation process between learning resources and learners' needs. Through the attention mechanism, this model effectively improved the accuracy of personalized recommendations and its adaptability.

The experimental results revealed several key findings: a) The model proposed in this study demonstrated superiority in comparison with other algorithms. b) Feature fusion significantly increased the convergence speed of the adaptation algorithm. c) The performance of the adaptation algorithm was influenced by the number of fused features, indicating a direct impact of feature selection and fusion strategies on the algorithm's effectiveness. d) The capacity of various types of resources significantly influenced the success rate and the average accuracy of adaptation, highlighting the importance of resource diversity in personalized learning.

This study illustrates how deep learning models enhance the effectiveness of adapting online learning resources, particularly in personalized learning. The results indicated that the incorporation of deeply integrated content features and attention mechanisms significantly improved adaptation performance, which is of great importance for the advancement of more intelligent and responsive educational technology products tailored to learners' needs.

In summary, an innovative model structure that combines the SA-CNN and deep metric attention mechanisms was proposed to effectively address the challenge of adapting online learning resources. The research may rely on specific types of datasets and features, and its generalizability and extensibility require further validation. Experiments have not yet been verified in a broader educational environment, indicating potential environmental dependencies. Future research directions include exploring the adaptability of the model across various educational fields and cultural backgrounds. Additionally, there is a need to further optimize the model structure to handle more complex learning scenarios and a diverse array of learning resources.

## 6 ACKNOWLEDGMENT

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