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Research Article

The Application of Graph Neural Network Based on Edge Computing in English Teaching Mode Reform

Yunlong Huang[1] and Yanqiu Wang[2]

[1]School of Applied Foreign Languages, Liaodong University, Dandong, 118001 Liaoning, China
[2]Center of Modern Education Technology, Liaodong University, Dandong, 118001 Liaoning, China

Correspondence should be addressed to Yunlong Huang; huangyunlong@elnu.edu.cn

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The latest developments in edge computing have paved the way for more efficient data processing especially for simple tasks and lightweight models on the edge of the network, sinking network functions from cloud to edge of the network closer to users. For the reform of English teaching mode, this is also an opportunity to integrate information technology, providing new ideas and new methods for the optimization of English teaching. It improves the efficiency of English reading teaching, stimulates the interest of English learning, enhances students' autonomous learning ability, and creates favorable conditions for students' learning and development. This paper designs a MEC-based GNN (GCN-GAN) user preference prediction recommendation model, which can recommend high-quality video or picture text content to the local MEC server based on user browsing history and user preferences. In the experiment, the LFU-LRU joint cache placement strategy used in this article has a cache hit rate of up to 99%. Comparing the GCN-GAN model with other traditional graph neural network models, it performs caching experiments on the Douban English book data and Douban video data sets. The GCN-GAN model has a higher score on the cache task, and the highest speculation accuracy value F1 can reach 86.7.

1. Introduction

In recent years, applications based on deep learning have brought great improvement to people's lives. People are more and more interested in the extension of graph deep learning methods. With the success of many factors, a new research hotspot "Graph Neural Network (GNN)" came into being. In the era of Internet of Everything, it is a big challenge to run computational intensive deep learning algorithms on edge devices with limited resources.

Under the background of educational informationization, the introduction of advanced technology into the classroom is also an inevitable development trend. In view of the disadvantages of traditional English classroom teaching, new technology can provide new ideas and methods for the reform of English teaching mode. Traditional English reading teaching mainly has problems such as lagging teaching concepts, single teaching materials, limited teaching content, and low students' sense of self-efficacy. With the support of information technology, English teaching mode reform is carried out to get rid of the shortcomings of traditional English teaching mode, so as to expand students' knowledge and cultivate students' reading ability.

This article designs a platform that can intelligently recommend learning content by combining MEC technology and graph neural network algorithms. It deepens teachers' understanding of information-based teaching, promotes the renewal of teachers' teaching concepts and reflections on teaching practice, and finally realizes the in-depth development of English teaching reform at the junior high school stage.

The development of various intelligent technologies has promoted the reform process of education and teaching. The innovations of this paper are as follows: First, this paper adopts the LFU-LRU joint cache placement strategy and proposes a new online joint collaborative cache and processing algorithm, which can improve the cache hit rate. The second is to introduce the graph attention mechanism into the graph convolutional neural network to complement the functions to improve the performance of the graph neural network model. Thirdly, based on edge computing and machine learning technology, an adaptive recommendation system for English teaching oriented to users and content is constructed.

2. Related Work

In order to reduce the transmission delay of network services, edge computing has attracted more and more attention from the industry and academia, and due to the continuous development of deep recognition technology, running deep learning algorithms on edge devices with limited resources has become a research hotspot. Zhang Y. et al. proposed a computing resource allocation scheme for IoV mobile edge computing scenarios based on deep reinforcement learning network. They determined the task resource allocation model in the corresponding edge computing scenario, with the minimum total computing cost as the objective function and established the mathematical model of task offloading and resource allocation [1]. The resource allocation model they established can indeed effectively cope with the problem of slow data return, but the research does not make empirical application of the model's use effect in practical applications; it is only a theoretical explanation. Zhang J. et al. proposed a new data layout method for edge-oriented computing vector processor with specific neural network model and applied it to feature mapping. They proposed a method of parallelizing matrix convolution calculation in three-dimensional space to improve access efficiency [2]. The data layout method proposed by Zhang J.'s research can greatly improve the efficiency of edge computing for data access, but its use of neural network algorithms needs to be further optimized. Based on the graph convolutional neural network, Ahmad et al. proposes a graph sparsity technique that uses effective edge resistance to better model global context information and eliminate redundant nodes and edges in the graph. In addition, they combined self-attention graph pools to preserve local attributes [3]. Xu proposes an edge computing based on a deep reasoning framework, which has the privacy of local differences in mobile data analysis. The deep learning model is used to minimize data and adaptively inject noise to confuse the learned features, thereby forming a new protective layer to resist sensitive inference [4]. His research is mainly for edge computing, and there is certain research progress, but the feasibility of the scheme used has yet to be verified. Liu and He developed and designed a system software based on cognitive computing in the embedded ARM server system and also built the related system database. This system is mainly used in the reform of teaching technology, which can improve the intelligence of teaching methods and achieve low error rate in the transmission of teaching resources [5]. Its research is a great progress for the application of artificial intelligence in the reform of teaching mode, and it also provides new ideas for the research of this article. Wei et al. studied the computational offloading problem of mobile users in mobile edge computing wireless cellular networks and used a model-free reinforcement learning (RL) framework to describe and solve the computational offloading problem. Each mobile user interacts with the environment and chooses local computing or edge computing according to its status [6]. The research is mainly aimed at the mobile user computing offloading problem of mobile edge computing and provides a more adaptable solution. However, the research process is too complicated, and the actual application effect may not be good.

3. The Application Research Method of Graph Neural Network Based on Edge Computing in the Reform of English Teaching Mode

3.1. Edge Computing Technology. Edge computing is a new technology for the Internet of Things, which lies between physical entities and industrial connections. Its model diagram is shown in Figure 1. It can be seen that it is an open platform for users and content, which starts the response at the edge of the cloud platform, can meet the service requirements of various organizations and industries in real-time business, intelligent application, and data security protection, and has faster response speed and convenient access than the cloud platform [7, 8]. In essence, edge computing is an application mode that integrates the core technologies of network, computing, storage, and application to provide the nearest service on the side close to things or data sources.

3.1.1. Basic Concepts and Architecture of MEC Mobile Edge Computing. This article mainly studies the mobile edge computing (MEC) technology, which is a new technology based on the 5G evolution architecture. MEC can be understood as a cloud server running on the side of the access network. Because MEC is closer to users, using the powerful storage and computing capabilities of MEC servers, users can offload computationally intensive tasks to MEC for execution. Edge computing can provide IT services, cloud computing, and storage functions in wireless network services. Network delay can be reduced to a considerable extent, ensure efficient network operation and service delivery, and improve user experience [9, 10]. MEC cloud server provides computing resources, storage resources, and connectivity and provides a highly distributed computing environment close to mobile users. In general, the characteristics and advantages of MEC can be summarized in the following aspects: First, MEC is close to the information source, which helps to obtain and analyze the key information in big data. Second, because the edge service runs close to the terminal device, it can greatly reduce the delay.

Regarding the MEC reference architecture, the MEC architecture can be divided into three parts: the network

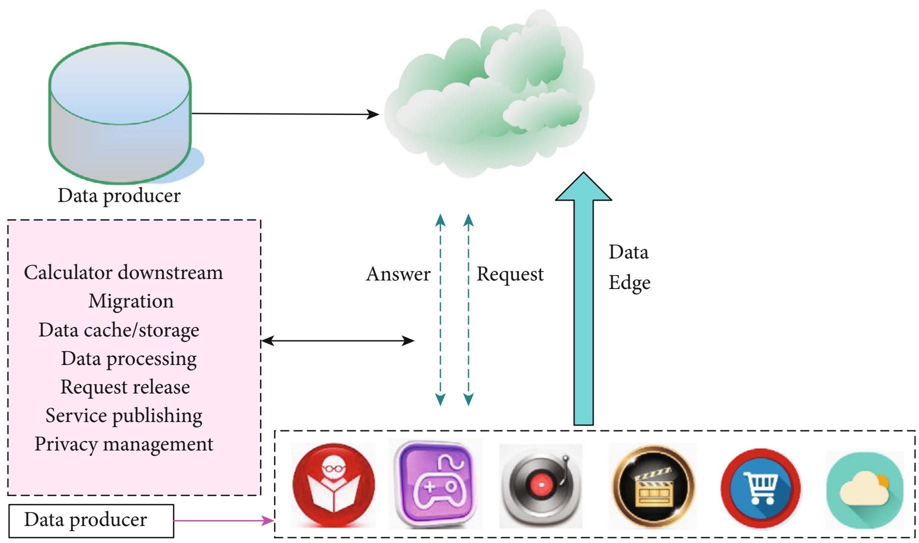

Figure 1: Edge computing model.

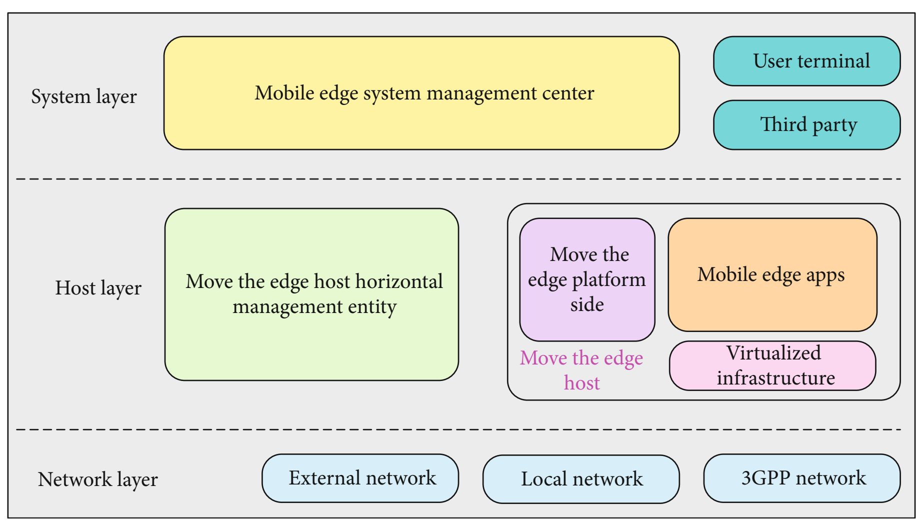

Figure 2: MEC basic network architecture.

layer, the host layer, and the system layer, as shown in Figure 2. Among them, the top layer is the level management entity of the MEC system, responsible for the overall management of the MEC system. In the middle is the MEC host layer, including the MEC host and the mobile edge host horizontal management entity. MEC hosts are further divided into mobile edge applications, MEC platforms, network function virtualization (NFV) infrastructure, etc. The network layer mainly includes cellular and internal and external networks [11].

3.1.2. Content Caching Network System Based on MEC Architecture. Different from mobile cloud, in MEC framework, the function of cloud data center is migrated to the edge of mobile network, so it can directly process and respond to service requests in the network accessed by users. The content caching network model of the mobile edge computing service architecture is given in Figure 3. The mobile user establishes a connection with the mobile edge network through the base station. Mobile operators deploy multiple MEC service facilities at the edge of the network and deploy content to local EMC servers in advance, thereby adding computing, storage, and processing functions to the LTE wireless network. And it builds an open platform to implant applications to realize the information interaction between the wireless network and the business server [12, 13]. The local caches C1, C2, and C3 constitute a cooperative cache domain, and the BSSs (basic service sets, including various system management, data collection, and comprehensive settlement services) in between are connected by optical fibers, and each MEC can communicate with each other and share content [14].

3.1.3. MEC Caching Mechanism Based on Intelligent Prediction of Content Popularity. The basic idea of content intelligent prediction MEC cache mechanism is to characterize the user's preference for the target content according to

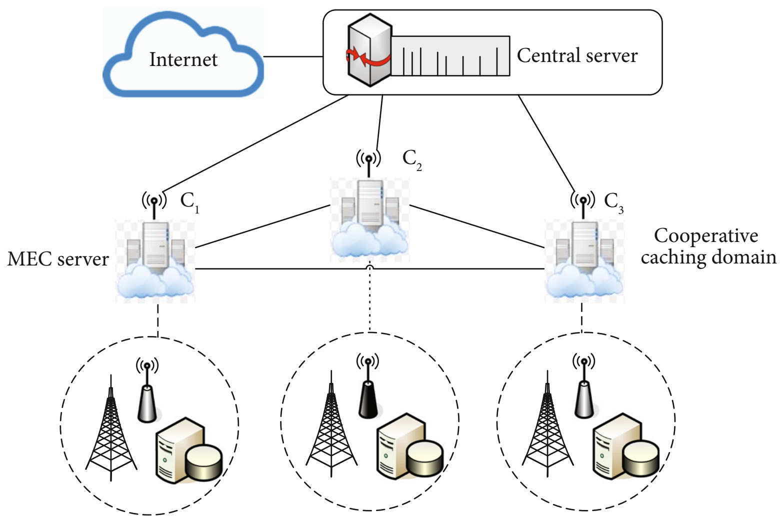

FIGURE 3: EMC content caching network model.

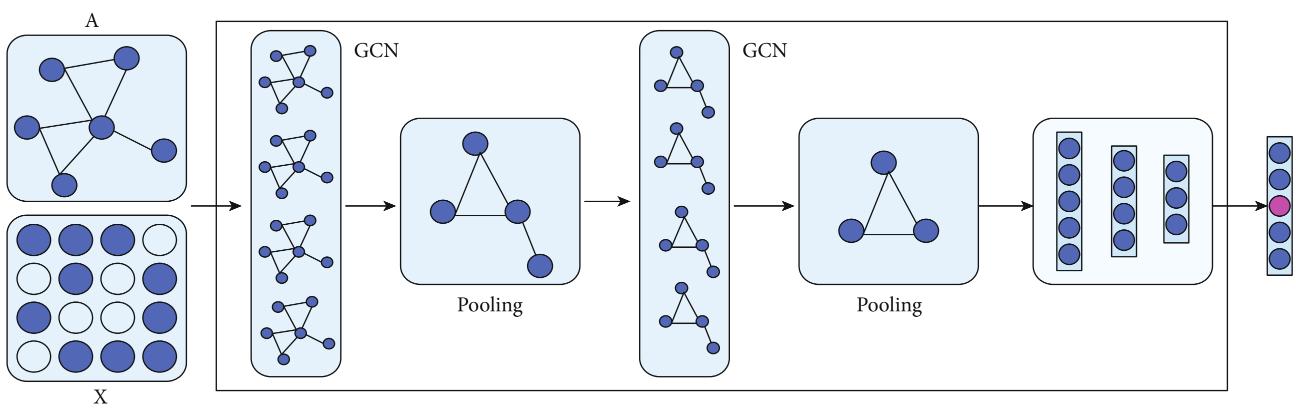

FIGURE 4: GCN network structure.

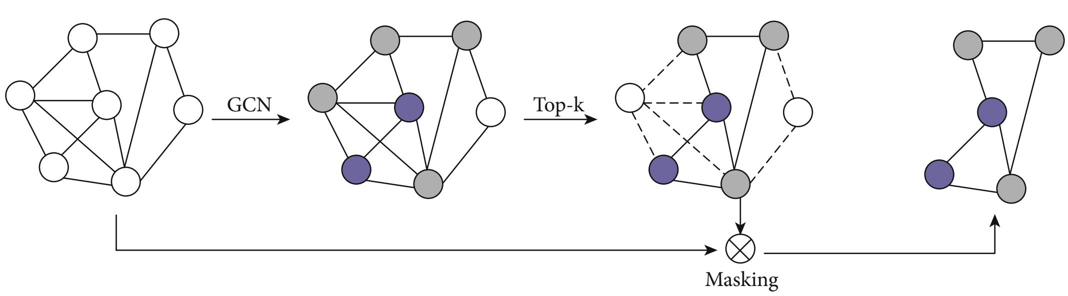

FIGURE 5: Pooling process based on graph attention mechanism.

the historical browsing data of the target content in the same time period in the local and other writing MEC service domains [15]. The basic process is as follows: First, classify the data content in the same collaborative cache domain with the similarity of content access features as an indicator. Second, use the same type of historical access data as the content to be predicted as the training set, and use the transfer learning idea to model and analyze.

Before using the migration learning idea to estimate the popularity of content, it is necessary to classify the content accessed by users. The classification method of this study is K-means clustering algorithm, assuming that the cluster sample data set is

$$M = \left\{ m_j \mid m_j \in R^2, j = 1, 2, 3, \cdots, L \right\}, \tag{1}$$

where m_j characterizes the access characteristics of the content in a certain period of time. The static popularity V_j and the access change rate C_j of the content Q_j in

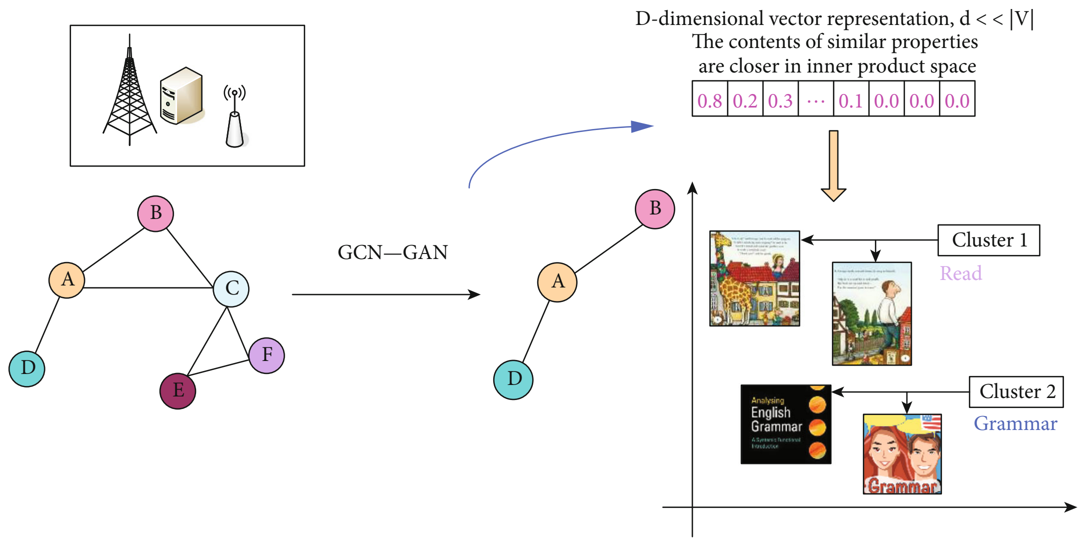

Figure 6: Application of MEC-GNN (GCN-GAN) in English content recommendation system.

Table 1: QoS level parameters.

Index requirements business type	FTP service	HTTP service	Voice service	Video service
QoS level	1	2	3	4
Bit error rate requirements	10^{-5}	10^{-5}	10^{-4}	10^{-4}
Delay limit	N/A	N/A	30 ms	10 ms
Transmission speed	89 kb/s	15 kb/s	8 kb/s	63 kb/s
Packet loss rate	N/A	N/A	0.01	0.01

the MEC system are used to describe the access characteristics, namely

$$m_j = \left(V_j, C_j\right),$$
$$V_j = \sum_{a=1}^{A} V_{a,j}, \tag{2}$$
$$C_j = \frac{\sum_{a=1}^{A} S_{a,j}(t) - \sum_{a=1}^{A} S_{a,j}\left(t'\right)}{\sum_{a=1}^{A} S_{a,j}(t)},$$

where $S_{a,j}(t)$ represents the current time period, the number of times the content Q_j has been accessed, and t' represents the previous time period. Suppose M is divided into K clusters, which are represented by $w_1, w_2, \ldots, w_k$. The centers of each cluster are denoted by $f_1, f_2, \ldots, f_k$ in turn. Given content Q_j, assuming f_i is its cluster center, then

$$\left\|m_j - f_i\right\| = \min \left\|m_j - f_k\right\|. \tag{3}$$

In order to make the access features of the content classified into the same category have high similarity, the distance value should be made as small as possible.

Table 2: MEC communication system simulation parameters.

Parameter	Value
Macro base station capacity	6 MHz
Small base station capacity	1 MHz
MEC server capacity	12 MHz
Number of cells	5
Cell radius	2 km
Number of cell channels	25
Subcarrier bandwidth	11.8725KHz
Number of data subcarriers	412
Maximum length of task queue	6
Doppler bias	5-25 Hz
White noise power	-164 dBm/Hz
Zipf—v	0.8

The next step is the prediction process. Q is divided into k groups. The total content contained in each group is bi. Given a predicted target $V(t)$, the target domain is defined as the historical access data of the predicted target content in the local MEC U_n server before time t. The source domain is the historical access data of each content in each category under each MEC in the collaborative cache domain [16, 17].

The predicted popularity of content q_i in the next time period U_a at time t is

$$\widehat{V}(t+\Delta t) = d_{n,k} * V_{n,k}^{T}(t) + \sum_{\substack{l=1 \\ l \neq n}}^{N} d_{l,k} * V_{n,k}^{S}(t), \tag{4}$$

where $d_{n,k}$ is the learning factor of the nth data content of the k-th category, $V_{n,k}^{T}(t)$ represents the popularity of the content in the U_n server in the previous time period of t, and $V_{n,k}^{S}(t)$ represents the popularity of each collaborative cache area in the source domain in the previous time period.

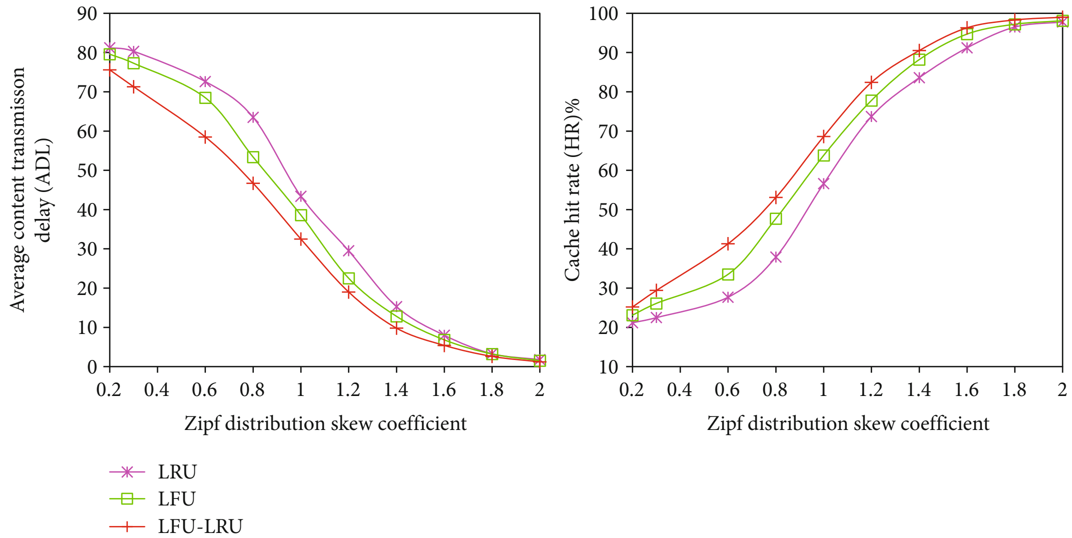

Figure 7: Performance comparison of each cache mechanism under the change of skew coefficient.

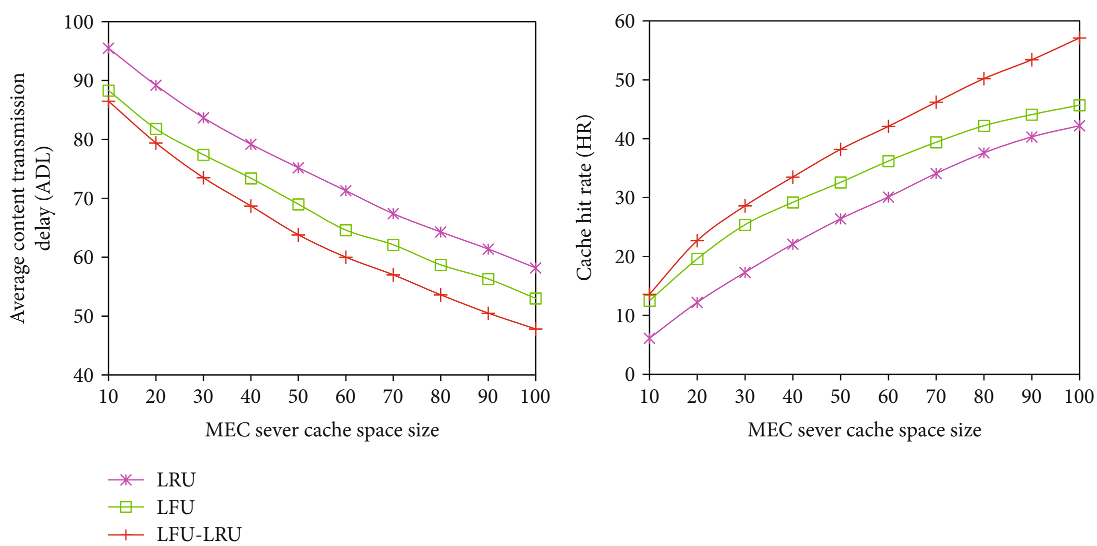

Figure 8: Performance comparison of various cache algorithms under changes in cache space.

Therefore, in order to make the predicted value closer to the true value, it is necessary to obtain the optimal $d_{n,k}$ value.

In wireless network communications, the most commonly used caching strategies are LFU and LRU, so these two caching strategies have certain limitations. The basic starting point of LFU is that if a certain data is used very few times in the recent period of time, then the probability of being accessed in the short term in the future will also be very small. The basic starting point of LRU is that if a certain piece of data has been accessed recently, the user will have a higher probability of requesting the content in the future compared to data that has not been accessed. Therefore, this article considers combining the two solutions and proposes a more flexible replacement strategy, namely, the LFU-LRU joint strategy. This scheme flexibly adjusts the proportion of LFU and LRU by weighing the factor CRF. The closer the CRF value is to 0, the strategy tends to LFU, and the closer to 1, the more it tends to LRU [18]. In summary, the LFU-LRU joint caching strategy is if the user's request is not cached in the local BS, the video will be retrieved from the adjacent cache or the source content server. Then, it saves the content in the cache on the local server. If there is not enough space, then the least recently used entry is moved out of the cache to make room for newly added content.

In the MEC server cache area, each data block saves an attribute representing the weight of the CRF. The CRF value of the resource file can be defined as

$$\mathrm{CRF}(r) = f(0) + f(\mathrm{t_c} - \mathrm{LA}(r) *), \quad f(x) = \frac{\lambda x}{2}. \tag{5}$$

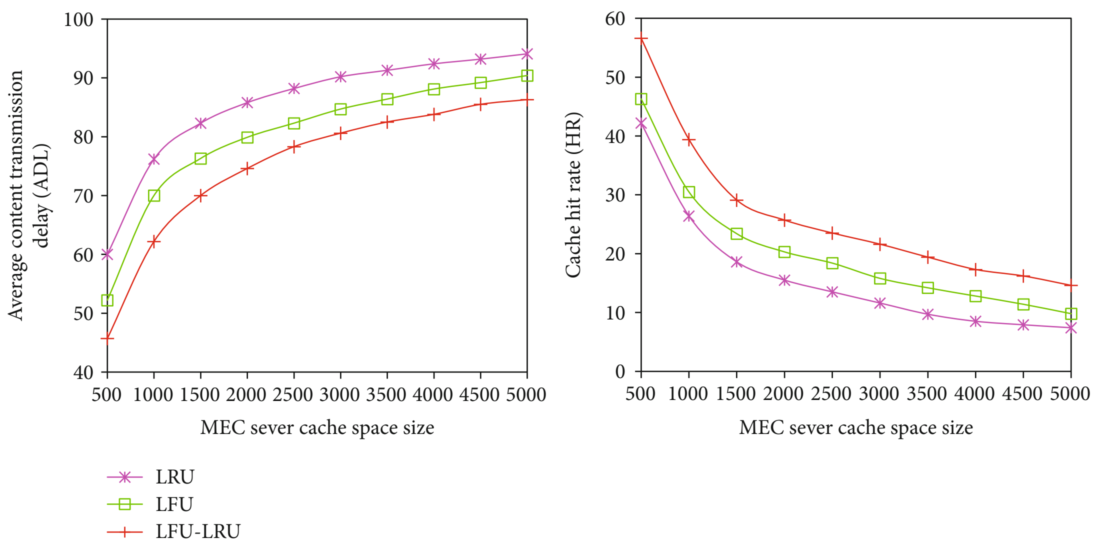

FIGURE 9: Performance comparison of various caching algorithms under changes in the number of service contents.

TABLE 3: The performance of different models on the miniImagNet data set.

	ROU—AUC	PR—AUC	F1
GAT	78.16	79.02	80.28
GCN	81.65	82.87	83.01
DeepWalk	76.44	79.25	78.05
GCN—GAN	83.52	84.71	85.59

And they, respectively, represent the number of accesses to file r in the previous time period and the CRF value of file r.

3.1.4. Performance Indicators. This study examines the performance of the LFU-LRU joint caching strategy based on the MEC architecture proposed in this paper from three performance indicators. They are the average content transmission delay (ADL), cache hit rate (HR), and average content transmission overhead (ATC).

For the edge computing system, because its advantage is convenience and quickness, the requirement for system delay is higher. In MEC system, ADL is the key index to measure the quality of user experience. The ADL expression is

$$\mathrm{ADL} = \sum_{n=1}^{N}\sum_{i=1}^{L} V * \left\{ t_n + t_{n\boxtimes k}(1 - m_{n,i}) * \left[1 - \prod_{\substack{a=1 \\ a\neq n}}^{N} (1 - m_{a,i}) + t_{0,n} * \prod_{a=1}^{N}(1 - m_{a,i}) \right] \right\}. \quad (6)$$

The transmission delay of the data content directly obtained from the local MEC U_n is represented by t_n, and the minimum transmission delay from other MECs that cache the target content to U_n in the collaborative cache domain where U_n is located is represented by $t_{n\boxtimes k}$. The transmission delay of data content from the remote service center to the local MEC is $t_{0,n}$.

In the MEC mobile edge computing service system, when a user sends a service request, if the requested content is backed up in the local or collaborative cache, it is sent to the user, which is called a cache hit. If there is no backup, it needs to be obtained from the remote central server and then sent to the user, which is called cache miss. Let E represent the amount of content requests received by the cooperative cache domain and W represent the amount of missed requests, then the cache hit rate can be expressed as

$$\mathrm{HR} = 1 - \frac{W}{E}. \quad (7)$$

The average content transmission cost expression is

$$\mathrm{ATC} = \sum_{n=1}^{N}\sum_{i=1}^{L} V_{ni} * \left(y_{n,i}^{1} + y_{n,i}^{2}\right). \quad (8)$$

When the content is not cached locally, but in the collaborative cache area, the intradomain transmission overhead generated by selecting the shortest distance to return the content to the user is represented by $y_{n,i}^{1}$. If there is no backup of the content in the collaboration area, the remote control center will send the content back to the user, which will cause extradomain overhead, which is represented by $y_{n,i}^{2}$.

3.2. Graph Neural Network Algorithm (GNN). Graph neural network is a way to convert data into graphs or directly process graph data. By exploring the information transmission process of the nodes in the graph, researchers can mine the information correlation characteristics within the data. The graph neural network aims to use the adjacency relationship between nodes in the network to learn low-dimensional vector representations for each node through random walks,

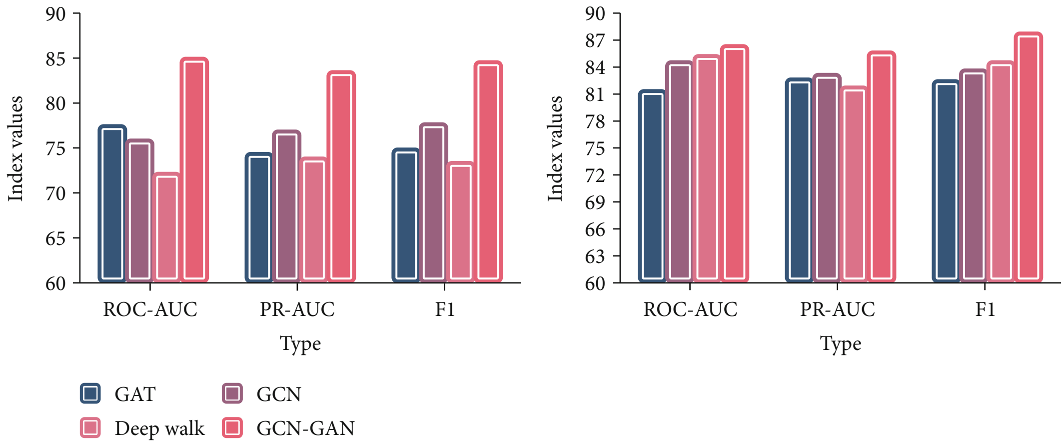

Figure 10: Cache prediction accuracy results of various learning mechanisms.

sampling aggregation and other methods. The similarity between vectors is widely used in tasks such as recommendation and link prediction because it can reflect the similarity of nodes in the network. Graph neural networks are divided into two categories: graph neural networks based on neighbor aggregation and graph embedding. Common graph neural network algorithms include graph convolutional neural network (GCN), graph attention mechanism (GAN), and graph isomorphic network (GIN). A large number of graphs and video data are also involved in English teaching, so the introduction of graph neural network algorithms can push more targeted teaching materials for students and teachers. It can greatly reduce the teacher's burden of preparing lessons and improve students' learning skills. This article mainly introduces GCN and GAN graph neural network algorithms.

3.2.1. Graph Convolutional Neural Network Algorithm (GCN). The graph convolution network extends the convolution operation from traditional data to graph data, and its main purpose is to enable the graph neural network model to effectively learn the node features in the graph. The principle of GCN is to aggregate feature information from the neighborhood. When running at the node level, the graph pooling module can be interleaved with the graph convolutional layer to transform the graph pool into a high-level substructure. The algorithm flow of GCN is as follows: The first is input, and each node sends its transformed characteristic information to neighboring nodes. Secondly, self-encoding expresses the node as a low-dimensional vector, and the neighboring node performs information fusion of characteristic information. At present, the main methods of GCN-based autoencoders are graph autoencoder (GAE) and adversarially regularized graph autoencoder (ARGA). Then, the node is subjected to linear transformation or nonlinear change to output new expression information [19]. The GCN structure is shown in Figure 4, including input, hidden, and output layers. The hidden layer is composed of a continuous convolution-pooling structure, which can be used to extract all levels of graph representation and perform graph classification tasks.

This model combines the characteristics of the spatial structure of the spectrum and graph topology in GCN and approximates the Laplacian matrix:

$$\begin{aligned} Y^{l+1} &= \delta\left(\widehat{E}^{-\frac{1}{2}}\widehat{Q}\widehat{E}^{-\frac{1}{2}} * Y^l W^l + a^l\right), \\ \widehat{Q} &= Q + I, \\ \widehat{E}_{ii} &= \sum_j \widehat{E}_{ij}, \end{aligned} \tag{9}$$

Among them, δ represents the activation function, E represents the matrix of the node, Q node represents the adjacency matrix, I is the identity matrix, l is the number of convolutional layers, and W^l and a^l are the training parameters and influence factors.

3.2.2. Graph Attention Mechanism (GAN)

(1) Graph Attention Network (GAT). This is a space-based graph convolutional network. The attention mechanism uses the attention mechanism to determine the weight of the node neighborhood when aggregating feature information. Its operation is defined as

$$H_i^t = \sigma\left(\sum_{j\in M_t} \alpha\left(H_i^{t-1}, H_j^{t-1}\right) W^{t-1} H_j^{t-1}\right), \tag{10}$$

where $\alpha()$ represents an attention function that can adaptively control the contribution of adjacent nodes j to i. GAT can also use a multiattention mechanism to deal with the weights of different subspaces:

$$H_i^t = \|_{f=1}^F \sigma\left(\sum_{j\in M_t} \alpha_f\left(H_i^{t-1}, H_j^{t-1}\right) W^{t-1} H_j^{t-1}\right). \tag{11}$$

(2) Graph Attention Model (GAM). In order to improve the system's ability to classify and identify graph data, the model provides a recurrent neural network model. The main purpose is to achieve adaptive access to the important node

sequence for processing graph information. The model is defined as

$$H_t = g_H(g_k(R_{t-1}, S_{t-1}, f ; \vartheta_k), H_{t-1} ; \vartheta_h), \tag{12}$$

where $g_H()$ is an LSTM network and g_k is a step network. Its function is to give priority access to neighbors with high priority of the current node and aggregate their information.

The advantage of GAT and GAAN is that they can adaptively learn the importance weights of neighbor nodes. However, the computational cost and memory consumption increase rapidly with the calculation of the attention weight between each pair of neighbors.

(3) GCN-GAN Joint Graph Neural Network Algorithm. The performance of GCN algorithm is excellent among many algorithms. However, in order to improve the information extraction effect of the structure in the downsampling mechanism, this research introduces the graph self-attention mechanism into the pooling mechanism of the graph convolution model, which can give higher weight to the information data that reflects the category. The specific model is shown in Figure 5. The model uses top-k interception in the pooling operation and uses the mask mechanism to filter nodes other than top-k. The advantage of this model is that it fully considers the topological structure of the node in the network and the inherent characteristic information of the node during the pooling process. The calculation principle of the structure output is

$$\begin{aligned}
Q(I) &= \sigma\left(\widehat{D}^{-\frac{1}{2}}\widehat{A}\widehat{D}^{-\frac{1}{2}} * HW_{\text{ztt}} + b_{\text{att}}\right), \\
\text{idx} &= \text{Top} - \text{rank } (Q, [\text{kN}]), \\
Q_{\text{mask}} &= Q_{\text{idx}}, \\
X_{\text{out}} &= X_{\text{idx}}, : \odot Q_{\text{mask}}, \\
A_{\text{out}} &= A_{\text{idx,idx}},
\end{aligned} \tag{13}$$

where H represents a node vector, W_{ztt} and b_{att} are the model parameter variables, Q_{mask} is a Boolean matrix, k is the proportion of pooled nodes, X_{out} is a new node feature matrix, and A_{out} is an adjacency matrix.

The target loss function selected in this model is a binary cross entropy function, which is optimized by the loss function of the variational automatic encoder module, namely

$$\text{loss} = \text{BCE}(y, \hat{y}) + \beta \times \left[0.5 \times \left(-\log \sigma^2 + \sigma^2 + \mu^2 - 1\right)\right]. \tag{14}$$

3.3. English Teaching Application of Graph Neural Network Based on Mobile Edge Computing

3.3.1. Disadvantages of Traditional English Teaching Mode. Teaching mode is the system structure of education and teaching methods constructed to achieve certain teaching objectives. It is based on certain education and teaching theory and practical experience. It is an intermediary that transforms relevant teaching theories into specific teaching activities and operating procedures and is the result of combining relevant teaching theories and practical frameworks with specific teaching situations.

This research takes the current situation of Chinese junior middle school English teaching mode as an example to illustrate. For a long time, China has mostly adopted the traditional "top-down" reading teaching model for English teaching. This model often adopts the method of word-for-word translation and comprehension of the article. It only sees the trees but not the forest. There is an obvious phenomenon of "language rather than culture." It is difficult for students to simply comprehend words to stimulate their interest in learning and to comprehend the true meaning of language, which has many disadvantages.

The gradual development of interactive English teaching mode provides a favorable opportunity for the reform of English teaching mode. Multimedia, computer network technology, and some artificial intelligence technologies have played an important role in education and teaching activities. It is important and necessary to carry out informatization teaching and then to promote the exploration of English teaching reform, which can further cultivate students' autonomous reading ability.

3.3.2. English Teaching Content Recommendation Based on Edge Computing-Graph Neural Network. The purpose of this article is to build a teaching platform around the difficulties of English teaching in junior high schools, supported by edge computing technology and graph neural network algorithms. According to the browsing records of pictures or videos of English knowledge by students and teachers, it can adaptively recommend English teaching content that students or teachers are interested in. The platform architecture is shown in Figure 6. Edge computing can quickly obtain user browsing data and cache the recommended content for the next time period locally. The graph neural network model can learn the characteristics of user browsing content and then can classify the content and can more accurately recommend relevant learning content to users [20, 21].

4. MEC—GNN English Teaching Content Recommendation Model Application Experiment

4.1. MEC Caching Mechanism Simulation Result Experiment

4.1.1. Simulation Parameter Design. The service domain level division and parameter setting are shown in Table 1. For different wireless service requirements, it can be divided into voice service, video service, FTP service, and HTTP service according to the type.

Since the performance of mobile edge computing is also affected by the range of the radiation area, the simulation parameter settings for the number of base stations, base station capacity, and MEC server capacity in the MEC communication system are shown in Table 2.

In the simulation experiment, only the content related to English learning is considered. Therefore, this type of content is predominant by default. For the collaborative cache domain model, consider that there are 4 MEC servers in a domain. This article intends to compare the optimized LFU-LRU algorithm with the pure LFU caching strategy and the pure LRU caching strategy. In this study, MATLAB is used for simulation experiments, and the control variable method is adopted. The performance comparison includes three aspects: first, the performance comparison of cache strategies under different Zif distribution skew coefficients; second, the cache performance comparison of cache strategies under different MEC server cache space sizes; and third, the cache performance comparison of cache strategies under different service contents. The experiment is mainly evaluated from the ability of daily living, human resources, and these two indicators.

The experimental results of the performance comparison of various caching mechanisms under the variation of skew coefficient are given in Figure 7. From the figure, it can be concluded that the optimized algorithm proposed in this experiment, LFU-LRU joint caching strategy based on MEC, has excellent caching performance among the three caching mechanisms under different skew coefficients of Zif distribution. It can be concluded that the caching performance of the caching mechanism increases as the skew coefficient increases, and popular content becomes more concentrated, so that the local EMC cache is more effective. And in the average content transmission delay (ADL) index comparison, the LFU-LRU joint caching strategy value is always smaller than the other two caching strategies. In the comparison of cache hit rate (HR) indicators, the cache hit rate of LFU-LRU is the highest, with a maximum of 99%. This means that the caching mechanism can more accurately predict the user's preference for browsing content and perform quick and convenient push. However, with the increase of the skew coefficient, the performance gap between several schemes gradually decreases. This is mainly due to the fact that when the skew coefficient is large, most user requests are concentrated on a small amount of content.

Figure 8 shows the performance comparison of the three caching mechanisms on ADL and HR under the MEC cache space change. The skew coefficient is 0.68, the range of MEC buffer space is set at 10-100, and the number of service contents in the network system is 1200. Under the three caching mechanisms, the results of the impact of cache space size changes on cache performance are given in Figure 8, namely, the trends of ADL and HR. Experimental results show that the average transmission delay of these cache mechanisms decreases with the increase of cache space, and the cache hit rate increases with the increase of cache space. Specifically, when the cache space is 50, the cache hit rate under this mechanism is 11.8% and 5.6% higher than that of LRU and LFU, respectively.

The cache space size of each experimental MEC server is 50, and the setting range of the number of service contents is 500 to 5000. The comparison results of the caching performance of the three caching mechanisms under the change of service contents are shown in Figure 9. Among the three caching strategies, the LFU-LRU caching mechanism proposed in this article is better than the other two. In summary, the LFU-LRU caching mechanism proposed in this paper can effectively improve the cache hit rate and reduce transmission overhead and content transmission delay.

4.2. MEC—GNN English Teaching Content Recommendation Platform Performance Experiment

4.2.1. Introduction to the Experimental Data Set. The experimental data set is divided into three categories. The first category is the miniImagNet data set, which is used to test the content classification performance of the platform. This data set is an excerpt from the ImageNet data set and is a small classification data set. The second and third types of data are Douban English book data and Douban video data, respectively, used to test the prediction accuracy of user preference transfer.

4.2.2. Experimental Results. This section of the experiment is mainly to test the performance of the English teaching content recommendation platform based on the MEC-based GNN (GCN-GAN) neural network proposed in this paper. It will be compared with some other deep learning methods and the situation of evaluating the target domain vector with three cache indicators of ROC-AUC, PR-AUC, and F1. The experimental results on the miniImagNet data set are shown in Table 3. It can be intuitively seen from Table 3 that the graph convolution-self-attention mechanism model based on edge computing proposed in this paper is the best for the classification of the data set. ROC-AUC, PR-AUC, and F1 values are higher than the corresponding experimental values of GAT, GCN, and DeepWalk.

The caching experiment results of several prediction models on the Douban English book data and Douban video data sets are shown in the left and right images of Figure 10, respectively. It can be seen from the experimental results that in this task, the user preference prediction and recommendation effect of English learning content based on learning transfer in this paper are the best. The other types of graph neural network models do not directly process graph structures in nature. Therefore, the performance score on the cache task is not too high. The GCN-GAN model has a higher score on the cache task, and the inference process is more efficient. The highest inference accuracy value F1 can reach 86.7.

5. Discussion

In this experiment, a cooperative caching mechanism for edge computing based on machine learning graph neural network is proposed. And it uses the method of transfer learning to predict the user's preference for push content. The experimental results show that the LFU-LRU caching strategy proposed in this research can effectively improve the cache hit rate and reduce the content transmission delay. The collaborative caching mechanism of graph neural network based on mobile edge computing in this paper is for the reform of English teaching mode, so the content of cache prediction is the English learning-related content browsed by teachers or students in the wireless network domain. In the prediction accuracy simulation experiment, the article compares the user preference prediction mechanism proposed in this paper with the other deep learning graph neural network models. Using ROC-AUC, PR-AUC, and F1, three cache indicators to evaluate the evaluation of the target domain vector, the results show that the optimized GCN-GAN model in this paper has a higher score on the cache task, and the inference process has a higher efficiency.

6. Conclusions

This article focuses on English teaching as the research object, using 5G mobile edge computing technology (MEC) and the graph neural network algorithm in the deep learning algorithm as modern technical support, constructing a wireless network cooperative caching mechanism. It can cache and recommend relevant meaningful learning content to users relatively accurately. This article proposes to integrate information technology into the whole process of English teaching, effectively improve students' comprehensive language ability, promote students' deep learning, and further verify the effect of junior high school English reading teaching through teaching practice. It is expected to provide guidance and reference for relevant practical research and promote the continuous improvement of new methods, new experiences, and new models of junior high school English teaching under the background of educational informationizion.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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