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Retraction

Retracted: Sharing Method of Online Teaching Resources of Spoken English Based on Deep Learning

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] W. Cai and Y. Peng, "Sharing Method of Online Teaching Resources of Spoken English Based on Deep Learning," *Journal of Electrical and Computer Engineering*, vol. 2022, Article ID 9520630, 9 pages, 2022.

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Research Article

Sharing Method of Online Teaching Resources of Spoken English Based on Deep Learning

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In order to improve the sharing effect of online teaching resources of spoken English, this paper considers the sharing of resources among tasks in a mixed criticality system based on fixed task priority scheduling. Moreover, this paper extends the traditional PCP protocol and proposes a resource sharing protocol suitable for the AMC scheduling model in a verifiable hybrid criticality system. In addition, with the support of deep learning, this paper analyzes the worst blocking time and the worst response time of the task at each stage. Finally, this paper analyzes the sharing methods of online teaching resources of spoken English in combination with deep learning methods and constructs a corresponding intelligent teaching resource sharing system. The experimental research results show that the sharing method of online teaching resources of spoken English based on deep learning has a good resource sharing effect.

1. Introduction

Computer-assisted spoken English has been used in various schools. Moreover, the spoken English teaching support system has been applied in colleges and universities [1]. However, most of the teaching materials of the existing network-assisted spoken English teaching platform for spoken English are simple and lack interactive functions. At the same time, the lack of content space based on HTML pages and the lack of unified standards or standards make it difficult to realize resource sharing, forming "island" resources [2]. Therefore, the development of online education resource sharing platform can not only improve students' autonomous learning ability, but also strengthen the interaction between teachers and students and reform the spoken English teaching model. The advent of the Internet era has also provided great convenience for online spoken English teaching. Many English training institutions or higher education have started to carry out online oral English teaching. Moreover, the credits obtained from this kind of online spoken English teaching can be used as the credits required for graduation, which gives the online spoken English teaching reliability. Although major colleges and universities have gradually developed online spoken English teaching, they are basically fighting each other. Nowadays, higher education students have a wide range of interests and hobbies, and different teaching methods may bring about great differences in knowledge acquisition [3]. Therefore, it is necessary to break through the threshold between major colleges and universities and link the spoken English teaching resources of major colleges and universities in the form of spoken English teaching points. The school can stipulate the credits that must be completed for each course or each type of course, but students can choose different spoken English teaching courses according to their own interests, which provides students with greater freedom and greater space. It is believed that, in the near future, fixed higher-level spoken English teaching classrooms and other resources will no longer be needed, and students only need to study independently to complete their studies. This will not only save resources for the school, but also increase more freedom for students, which is conducive to better learning for students.

Modern educational concepts are increasingly associated with computer technology. From the application of multimedia to the realization of remote oral English teaching, computer technology is powerfully injecting new ideas and development momentum into education, and the rapid development of computer networks has greatly realized resource sharing. The informatization of education is not only reflected in the daily oral English teaching, but also in the communication between teachers and students after class. The current oral English teaching mode of higher education often only sees teachers in the classroom and students after class. It is difficult to communicate with teachers, and related materials are only sent through emails, etc., which greatly restricts the delivery of information. Some colleges are studying and realizing the resource sharing of spoken English teaching venues, laboratories, and training bases. In fact, many colleges do not have their own internal learning-type spoken English teaching resource sharing system, and the management of spoken English teaching resources is chaotic. Even if there is a library of spoken English teaching resources, it is only a classified management of spoken English teaching resources, which has not been effectively used in practice, and teachers and students have not really participated in it. There is insufficient communication between teachers and students in oral English teaching. The connection between them is not strong. Therefore, there is an urgent need for a unique learning-oriented English oral teaching resource sharing system to change the current situation of oral English teaching management and communication.

Based on the above analysis, this paper analyzes the sharing method of online teaching resources of spoken English in combination with the deep learning method and constructs an online teaching resource sharing system of intelligent speech to improve the follow-up English teaching effect.

2. Related Work

In today's era, we should continue to improve and strengthen students' ideological work, which will be part of higher education [4].

With the growth of China's opening to the outside world and the acceleration of economic development, China's higher education, especially in recent years, has enabled more people to receive higher education, which is conducive to the progress of science and technology and the country's cultural quality.

The increase in the number of institutions in the management of schools also brings many problems. Student management also faces the complexity of work and diverse student personalities. In this case, the management of student management puts forward certain requirements which are quite high [5]. Therefore, the management of students must pay attention to and strengthen the student management of information technology. The main tasks of counselors include lack of management, household registration transfer, employment management, educational administration management, student funding, apartment management, and management of the Communist Youth League. These complex daily work increases a lot of pressure and burden on counselors. How to do this work well directly affects the work efficiency of counselors [6]. Therefore, the basic work of the counselor is very important. How to make college student management work is a very important issue as soon as possible. Using modern technology and complex daily work management, many students will reduce their work, and counselors will work under pressure, so that students can improve management level and management quality and improve work efficiency [7].

At present, the management model of most universities is relatively mature, and the digital construction of universities has achieved good results. The Massachusetts Institute of Technology (MIT) in the United States in the last century put forward the concept of digital campus construction through the efforts of a mature model of digital campus. With the help of governments in Europe and the United States, school teaching management has also been digitized, and the construction of digital campuses has been improved after completion [8]. The focus of the construction of informatization management information systems is on domestic campuses. Generally speaking, some universities started relatively early, such as Tsinghua University, which proposed the construction of campus networks and has basically completed a multifunctional digital education system. Through the research and analysis of the status quo of the teaching management system of domestic and foreign universities, it has been shown that the faculty ability of domestic and foreign universities has great advantages compared with the school. What is more, the advantages of the teaching assistant management system should also be used to assist in the management of the students' teaching situation in order to grasp the students' learning situation in real time [9].

Literature [10] believes that collaborative learning is a strategy for organizing students to learn through teams or groups. Literature [1] believes that collaborative learning is not only a learning strategy, but also an environment for consultation, discussion, communication, and information sharing for users in the learning process. The final form of its development is to form an educational community system. Literature [2] provides a good technical support environment for collaborative learning based on the concept of collaboration and sharing. Based on a socialized collaborative learning model, it provides an open socialized learning system and a socialized learning knowledge base, which is a very good environment. Literature [3] used Xiki in the teaching of graduate students, using a teaching method called subject-oriented immersive learning to immerse students in a fictitious online publishing house. In fictitious online publishing houses, they can develop e-books and teaching software.

In the learning environment realized by literature [4], learners can not only realize learning experience, share learning tasks, and quickly discover learners with relevant learning hobbies through the powerful functions of W Yu, but also continue to deepen through repeated iterations of knowledge and mastery of knowledge. Literature [5] uses

Wiki as an experiment on thesis collaboration platform. In this experiment, they took full advantage of W Yue's advantages of easy modification and timely storage, as well as the cultural essence of openness, equality, and sharing, and collaboratively constructed the undergraduate thesis on the Wiki platform.

3. Resource Sharing Algorithm Based on Deep Learning

This paper considers a system, which includes M shared critical resources $S = \{S_1, \ldots, S_k, \ldots, S_M\}$ and a mixed criticality task set $\tau = \{\tau_1, \ldots, \tau_N\}$ composed of N tasks. Each task τ_i has a set of parameters $\langle T_i, D_i, \overrightarrow{C}_i, P_i, p_i, L_i, l_i, \sigma_i\rangle$. In addition to the basic parameters T_i, D_i, $\overline{C_i}$, and P_i of the mixed criticality task model based on fixed priority scheduling introduced above, there are also two parameters $T_i, D_i, \overrightarrow{C}_i, P_i$, and l_i. Among them, $T_i, D_i, \overrightarrow{C}_i, P_i$ represents the set of shared resources used by task τ_i, and $T_i, D_i, \overrightarrow{C}_i, P_i$ represents the runtime priority. The runtime may change dynamically according to FCP rules, and $p_i \geq P_i$ (P_i represents the fixed priority assigned during the design phase). l_i represents the criticality at runtime. At runtime, it may change dynamically according to HLC rules, and $l_i \geq L_i$ ($T_i, D_i, \overrightarrow{C}_i, P_i$ is the fixed criticality specified in the design stage). Lowercase variables indicate parameters that can change dynamically at runtime, and uppercase variables indicate constant parameters. We use the term high-criticality task to mean a task with a fixed criticality ($L_i = HL$). The term low-criticality task refers to a task that has a fixed criticality of low-criticality ($L_i = LO$) [6].

In addition, $Z_{i,k}$ is used to indicate the longest critical zone where task τ_i is protected by semaphore S_k, and $\delta_{i,k}$ indicates the maximum length of critical zone $Z_{i,k}$. According to good software engineering practices, critical sections are usually a short section of code that does not contain complex control flow. Therefore, we assume that the length $\delta_{i,k}$ of each critical section is the same at different criticality levels.

Definition 1 is as follows: active tasks are tasks that have not been terminated. When the system is in low-criticality mode, all high-critical tasks and low-critical tasks are active tasks. When the system is in the high-criticality mode, only high-critical tasks are active tasks. In the criticality mode transition phase, high-critical tasks and low-critical tasks that are accessing resources that may be accessed by high-critical tasks are active tasks.

Each semaphore S_k has a static priority ceiling $PC(S_k, LO)$ in low-criticality mode. It is defined as the highest priority of all tasks that may access semaphore S_k in low-criticality mode [7]:

$$PC(S_k, LO) = \max_{\tau_i \in \tau}\{P_i | \tau_i \text{ needs } S_k, L_i = HI \vee LO\}. \tag{1}$$

Each semaphore S_k has a static priority ceiling $PC(S_k, HI)$ in the high-criticality mode, which is defined as the highest priority of all high-critical tasks (that is, fixed criticality is a task with high criticality) that may access the semaphore S_k in the high-criticality mode:

$$PC(S_k, HI) = \max_{\tau_i \in \tau}\{P_i | \tau_i \text{ needs } S_k, L_i = HI\}. \tag{2}$$

Each semaphore S_k has a dynamic priority ceiling $\mathrm{d}PC(S_k)$, which is defined as the highest priority of all active tasks that may access S_k:

$$\mathrm{d}PC(S_k) = \max_{\tau_i \in \tau}\{P_i | \tau_i \text{ needs } S_k, \tau_i \text{ is currently active}\}. \tag{3}$$

Obviously, in low-criticality mode, $dP\ C(S_k) = PC(S_k, LO)$. In high-criticality mode, $dP\ C(S_k) = PC(S_k, HI)$. In the criticality transition stage, $PC(S_k, HI) \leq dP\ C(S_k) \leq PC(S_k, LO)$[8].

The dynamic system priority ceiling (dSPC) is defined as the highest dynamic priority ceiling of critical resources currently being used by all active tasks:

$$dS\ PC = \max_k\{dP\ C(S_k) | S_k \text{ is currently held}\}. \tag{4}$$

Each critical resource S_k also has a static criticality ceiling $\mathrm{CC}(S_k)$, which is equal to the highest criticality level of all tasks that may use critical resource S_k:

$$CC(S_k) = \max_{\tau_i \in \tau}\{L_i | \tau_i \text{ needs } S_k\}. \tag{5}$$

The scheduling rules using the HLC-PCP protocol in the AMC-based hybrid criticality scheduling strategy are as follows:

R1: at any moment, the system can be in one of three modes: low-criticality mode ($\Theta == LO$), high-criticality mode ($\Theta == Hl$), or criticality mode transition stage ($\Theta == MCP$). Initially, the system is in low-criticality mode ($\Theta == LO$).

R2: when the task does not access any semaphore, its dynamic priority and dynamic criticality level are, respectively, equal to its fixed static priority and criticality level ($p_i = P_i$ and $l_i = L_i$). During the operation of the system, the dynamic priority ceiling of each semaphore and the dynamic priority ceiling of the system are updated according to formula (3) and formula (4), respectively.

R3: when the system is in low-criticality mode ($\Theta == LO$), the ready task with the highest dynamic priority and dynamic criticality higher than or equal to low criticality will be scheduled for execution.

R4: when task τ_i wants to enter the critical zone protected by resource S_k, the HLC-PCP protocol inherits the traditional PCP protocol. We assume that S^* is the resource with the highest dynamic priority ceiling dPC(S^*) among all critical resources currently being used by other tasks (except τ_i itself). If τ_i's dynamic priority p_i is higher than dPC(S^*), it will lock resource S_k and enter the corresponding critical section. Otherwise, τ_i will be blocked by the low-priority task τ_j that is using the resource S^*, and τ_j will inherit the dynamic priority of τ_i, that is [9],

$$p_j = \max\left(p_j, \max_i\left\{p_i | \tau_i \text{ is blocked by } \tau_j\right\}\right). \tag{6}$$

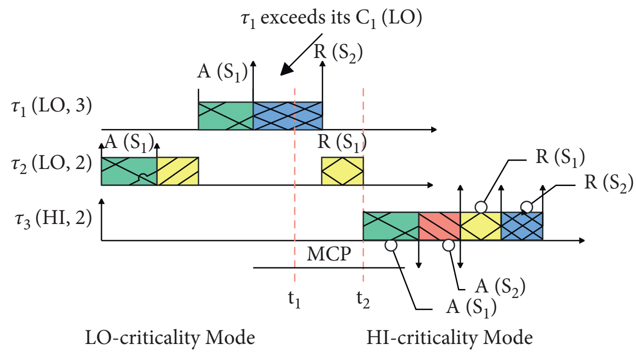

Figure 1: In the criticality mode transition stage, the high-criticality task τ_3 is blocked by the low-criticality tasks τ_1 and τ_2.

After τ_j releases the resource S^*, τ_j's dynamic priority p_j is updated again according to formula (6).

R5: when task τ_i enters the critical zone protected by semaphore S_k, the criticality l_i will be updated to $\max(l_i, CC(S_k))$ when task τ_i is running. Once τ_i releases the semaphore, the values of S_k and l_i will be restored to the values before the semaphore S_k was locked (the HLC (Highest-Locker Criticality) in the naming comes from this rule).

R6: when the execution time of the job (from any task τ_a) being executed exceeds its WCET estimated value Ca(LO) in low-criticality mode and has not ended, if a low-criticality task is using critical resources that may be accessed by a high-criticality task, the system will enter the criticality transition phase ($\Theta \leftarrow MCP$). When the system is in the criticality transition phase ($\Theta == MCP$), high-critical tasks and low-critical tasks whose criticality is high-critical during runtime will still be executed, while other low-critical tasks will be immediately discarded. When the system is running, once the low-criticality task T with the criticality $l=$HI releases the resources shared with the high criticality, and its runtime criticality l drops back to the low criticality ($l_i = LO$), it will be immediately discarded. When all low-critical tasks are discarded, the system will enter a high-critical mode ($\Theta \leftarrow HI$).

R7: when the system is in the criticality transition phase or high-criticality mode ($\Theta == MCP \vee HI$), at each moment, the task T with high criticality ($l_i = HI$) and the highest runtime priority p will be selected for execution at runtime criticality.

As shown in Figure 1, no matter the system is in any criticality mode, high-criticality tasks τ_3 and τ_4 can always complete their critical regions. In addition, after the criticality mode changes, the low-criticality task τ_2 will not be terminated until the critical region protected by the resource S_1 shared with the high-criticality task τ_3 is completed.

Figure 1 is used to illustrate the properties 3 and 4 of the HLC-PCP protocol. Tasks τ_1 and τ_2 are low-critical tasks, and task τ_3 is high-critical tasks. The fixed priority of τ_1 and τ_2 is higher than τ_3.

High-critical task τ_3 shares resources with low-critical tasks S_1 and S_2 respectively. Therefore, the criticality ceiling of resources S_1 and S_2 is $CC(S_1) = CC(S_2) = L_3 = HI$. In the low-criticality mode, task τ_2 locks resource S_1, and task τ_1 locks resource S_2. At time t_1, since the execution time of τ_1 exceeds $C_1(LO)$, the criticality mode of the system changes. At this time, tasks τ_1 and τ_2 are accessing resources Sz and S, respectively, and their dynamic criticality at this time is $l_1 = CC(S_2) = HI$, $l_2 = CC(S_2) = HI$. Therefore, tasks τ_1 and τ_2 will be able to continue execution until they release resources S_1 and S_2, respectively, and leave their critical regions before being discarded. In the interval of time $[t_1, t_2]$, task τ_3 is blocked by resources S_1 and S_2 once in the system criticality mode and blocked by tasks Z and C each ci once [10].

In the low-criticality mode, the pi-blocking of the job of task τ_i may come from the tasks of the sets $lpH(\tau_i)$ and $lpL(\tau_i)$. Therefore, the set γ_i^{LO} of critical regions that can produce pi-blocking on task τ_i in low-criticality mode is

$$\gamma_i^{LO} = \left\{Z_{j,k} \middle| \left(PC(S_k, LO) \geq P_i, \forall \tau_j \in lpH(\tau_i) \cup loL(\tau_i)\right)\right\}. \tag{7}$$

Since task τ_i can only receive pi-blocking once at most, the maximum pi-blocking time PB_i^{LO} that τ_i can receive in low-criticality mode. It is the length of the longest critical region that can cause pi-blocking to it, as shown below:

$$PB_i^{LO} = \max_{j,k}\left\{\delta_{j,k} \middle| Z_{j,k} \in \gamma_i^{LO}\right\}. \tag{8}$$

When the job of task τ_i arrives and completes in low-criticality mode, it can only be blocked by pi-blocking. Therefore, the worst blocking time for the task in the low-criticality mode is PB_i^{LO}.

In high-criticality mode, all low-critical tasks are discarded, and only high-critical tasks can be run. The pi-blocking of the job of task τ_i can only come from the task of set $lpH(\tau_i)$. Therefore, the set γ_i^{HI} of critical regions that can produce pi-blocking on task τ_i in the high-criticality mode is

$$\gamma_i^{HI} = \left\{Z_{j,k} \middle| \left(PC(S_k, HI) \geq P_i, \forall \tau_j \in lpH(\tau_i)\right)\right\}. \tag{9}$$

Since task τ_i can only be pi-blocked once at most, the maximum pi-blocking time PB_i^{HI} that τ_i can receive in high-criticality mode is

$$PB_i^{HI} = \max_{j,k}\left\{\delta_{j,k} \middle| Z_{j,k} \in \gamma_i^{HI}\right\}. \tag{10}$$

When the job of high-criticality task τ_i arrives and completes in high-criticality mode, it can only be blocked by pi-blocking. Therefore, the worst blocking time for task τ_i in the high-criticality mode is PB_i^{HI}.

In the criticality mode transition phase, we need to analyze the worst blocking time experienced by the transition operation of task τ_i.

X_i is used to represent the set of critical regions that can cause ci-blocking to task τ_i, including all critical regions that are protected by high-critical ceiling semaphores and belong to tasks in $lpH(\tau_i)$:

$$X_i = \left\{Z_{j,k} \middle| \tau_j \in hpL(\tau_i), CC(S_k) = HI\right\}. \tag{11}$$

Task τ_i can be blocked by ci-blocking at most once for each task τ_j that will bring criticality reversal. Therefore, the sum CB_i^l of the longest ci-blocking time caused by each task τ_i to τ_i is the upper bound of the maximum ci-blocking time that task τ_i can receive:

$$CB_i^l = \sum_j \max_k \left\{ \delta_{j,k} | Z_{j,k} \in X_i \right\}. \quad (12)$$

Task τ_i can be blocked by ci-blocking at most once for each semaphore S_k that will bring criticality inversion. Therefore, the sum CBA of the longest ci-blocking time caused by each semaphore S_k to τ_i is the upper bound of the maximum ci-blocking time that the task can receive:

$$CB_i^s = \sum_k \max_j \left\{ \delta_{j,k} | Z_{j,k} \in X_i \right\}. \quad (13)$$

Therefore, the worst ci-blocking time CB_i^{MS} that τ_i can receive is

$$CB_i^{MS} = \min\left(CB_i^l, CB_i^s\right). \quad (14)$$

$\mathrm{taskcrat_i}$ and $\mathrm{serncnt_i}$ are used to represent the number of tasks that can be ci-blocked for τ_i and the number of semaphores, respectively. Then τ_i can be blocked by at most min($\mathrm{taskcrst_i}$, $\mathrm{serncnt_i}$) critical sections at the same time. Therefore, the number of ci-blocks that τ_i can receive is min($\mathrm{taskcrst_i}$, $\mathrm{serncnt_i}$).

In the low-criticality mode and the criticality transition phase, the high-criticality task τ_i may be pi-blocked by all tasks from $lpH(\tau_i)$ and $lpL(\tau_i)$. In the high-criticality mode, the high-critical task τ_i can only be pi-blocked by the task from $lpH(\tau_i)$, and the low-critical tasks are discarded. Therefore, $PB_i^{MS} == PB_i^{LO} \geq PB_i^{HI}$. In addition, the transition operation of a high-critical task T will suffer the largest ci-blocking CB_i^{MS} in the criticality transition mode. Therefore, the worst blocking time that can be suffered by the transition operation of the high-critical task r is $PB_i^{LO} + CB_i^{MS}$.

In the low-criticality mode, we need to check the schedulability of each low-critical and high-critical task τ_i. The maximum blocking time of τ_i in low-criticality mode is PB_i^{LO}. Therefore, the worst response time R of task τ_i in low-criticality mode can be iteratively obtained by formula

$$R_i^{LO} = C_i(LO) + PB_i^{LO} + \sum_{\tau_j \in (hpH(\tau_i) \cup hpL(\tau_i))} \left\lceil \frac{R_i^{LO}}{T_j} \right\rceil \cdot C_j(LO). \quad (15)$$

In the high-criticality mode, we need to check the schedulability of each high-critical task τ_i.

In the high-criticality mode, the maximum blocking time of τ_i is PB_i^{HI}, and the worst response time R_i^{HI} of task τ_i in the high-criticality mode can be iteratively obtained by formula

$$R_i^{HI} = C_i(HI) + PB_i^{HI} + \sum_{\tau_j \in hpH(\tau_i)} \left\lceil \frac{R_i^{HI}}{T_j} \right\rceil \cdot C_j(HI). \quad (16)$$

In the transition phase of the system criticality mode, we only need to ensure the schedulability of the transitional job of each high-critical task τ_i. However, we no longer care about the schedulability of low-critical tasks, although some low-critical tasks can still be run. For a transitional job of a high-critical task τ_i, the maximum possible blocking time is $PB_i^{MS} + CB_i^{MS}$. The low-criticality task $\tau_k \in hpL(\tau_i)$ can only generate preemptive interference to τ_i in the low-criticality mode (it is worth noting that, in the transition phase of the system criticality mode, $\tau_k \in hpL(\tau_i)$ can only generate ci-blocking for τ_i). Therefore, the upper bound of the maximum preemptive interference that a low-criticality task $\tau_k \in hpL(\tau_i)$ can produce to a high-criticality task T is $\lceil R_i^{HI}/T_k \rceil \cdot C_k(LO)$.

Therefore, in the transition phase of the system criticality mode, the upper bound R_i^{MS} of the maximum response time of the transition operation of the high-criticality task T is

$$\sum_{j \in hpH(\tau_i)} \left\lceil \frac{R_i^{MS}}{T_j} \right\rceil \cdot C_j(HI) + \sum_{j \in hpL(\tau_i)} \left\lceil \frac{R_i^{LO}}{T_j} \right\rceil \cdot C_k(LO). \quad (17)$$

We calculate the worst response time of task τ_3 in the table. Task τ_3 can only be pi-blocked at most once. Task $\tau_4 \in lpH(\tau_3)$ and it shares resource $S_2\,(PC(S_2, LO) = 2 \geq P_3 = 2)$ with task τ_3. Therefore, the critical region $Z_{4,2}$ of task τ_4 can produce pi-blocking on task τ_3. According to formula (7), $\gamma_3^{LO} = \left\{Z_{4,2}\right\}$ can be obtained.

The maximum pi-blocking time experienced by task τ_3 is the length of critical zone $Z_{4,2}$, that is, $PB_3^{LO} = \delta_{4,2} = 10$. In the same way, $PB_3^{HI} = \delta_{4,2} = 10$ can be obtained.

Task τ_3 can only be pi-blocked in both low-criticality mode and high-criticality mode. Therefore, the worst blocking time of task τ_3 in low-criticality mode is $PB_3^{LO} = 10$, and the worst blocking time in high-criticality mode is $PB_3^{HI} = 10$.

According to formula (15), the worst response time R_3^{HI} of task τ_3 in low-criticality mode can be obtained as

$$\begin{aligned} R_3^{LO} &= C_3(LO) + PB_3^{LO} + \left\lceil \frac{R_3^{LO}}{T_1} \right\rceil \cdot C_1(LO) + \left\lceil \frac{R_3^{LO}}{T_2} \right\rceil \cdot C_2(LO) \\ &= 30 + 10 + \left\lceil \frac{R_3^{LO}}{100} \right\rceil \cdot 20 + \left\lceil \frac{R_3^{LO}}{200} \right\rceil \cdot 18. \end{aligned} \quad (18)$$

It is easy to calculate and get $R_3^{LO} = 78$.

According to formula (16), the worst response time RI of task τ_3 in high-criticality mode can be obtained as

$$R_3^{HI} = C_3(HI) + PB_3^{HI} + \left\lceil \frac{R_3^{HI}}{T_1} \right\rceil \cdot C_1(HI) = 40 + 10 + \left\lceil \frac{R_3^{HI}}{100} \right\rceil \cdot 30. \quad (19)$$

It is easy to calculate and get $R_3^{HI} = 80$.

In order to calculate the worst ci-blocking time experienced by the task in the criticality mode transition phase, since $hpL(\tau_3) = \{\tau_2\}$, and task $Z_{2,1}$ and task τ_3 share resource $S_1\,(CC(S_1) = HI)$, according to formula (11), the set of critical regions that can cause ci-blocking to task τ_3 is $x_3 = \left\{Z_{2,1}\right\}$.

Since there is only one critical section ($\mathrm{taskcrut_i} = \mathrm{semert_i} = 1$), we can get the maximum ci-

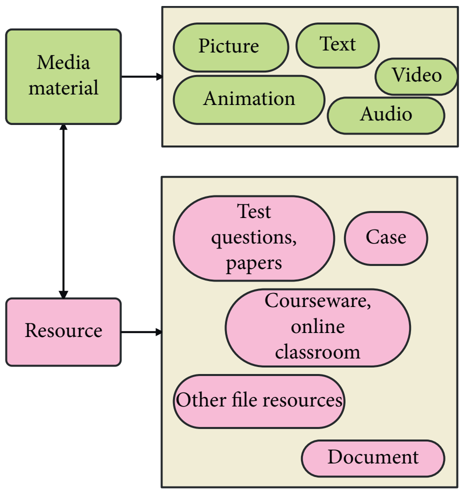

Figure 2: Classification of online teaching resources of spoken English.

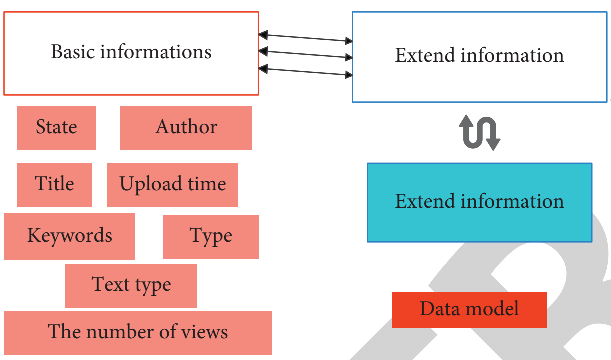

Figure 3: Data structure of online teaching resources of spoken English.

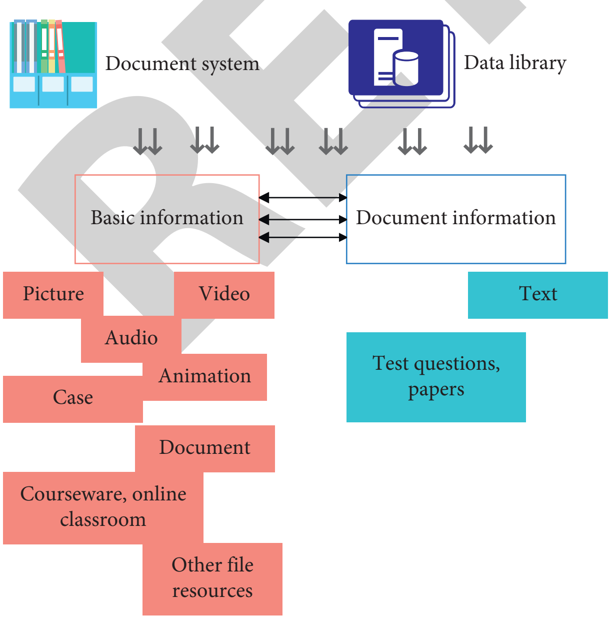

Figure 4: The storage structure of online teaching resources of spoken English.

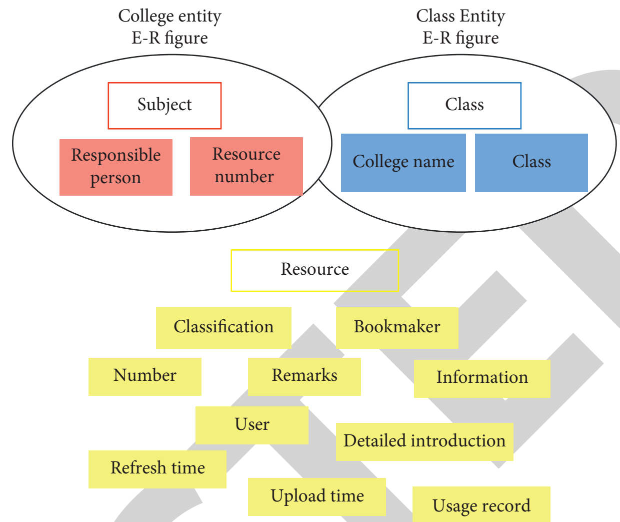

Figure 5: Entity E-R diagram of online teaching resources of spoken English.

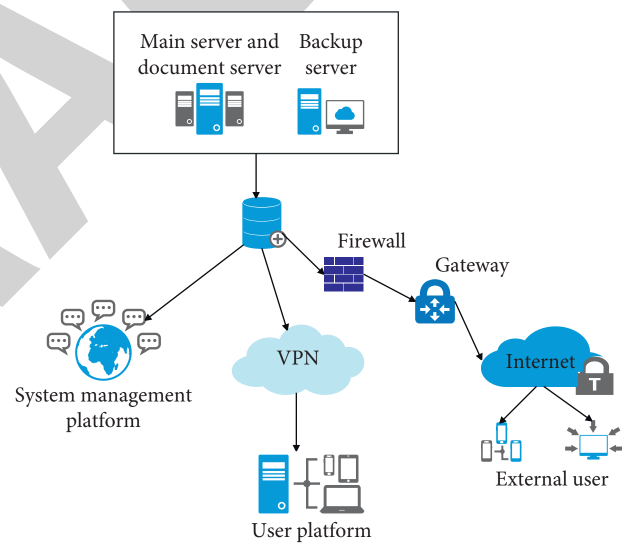

Figure 6: Schematic diagram of network deployment of online teaching resource management system for spoken English in colleges and universities.

blocking time that τ_3 can receive as the length of critical section $Z_{2,1}$, that is, $CB_3{}^{MS} = \delta_{2,1} = 10$.

According to formula (17), the worst response time R_i^{MS} of task τ_3 in the criticality mode transition phase can be obtained as

$$R_3^{MS} = C_3(HI) + PB_3^{LO} + CB_3^{MS} + \left\lceil \frac{R_3^{MS}}{T_1} \right\rceil \cdot C_1(HI) + \left\lceil \frac{R_3^{LO}}{T_2} \right\rceil \cdot C_2(LO)$$
$$= 40 + 10 + 10 + \left\lceil \frac{R_3^{MS}}{100} \right\rceil \cdot 30 + \left\lceil \frac{R_3^{LO}}{200} \right\rceil \cdot 18. \quad (20)$$

It is easy to calculate and get $R_3^{MS} = 138$.

The HLC-PCP resource sharing protocol is an extension based on the AMC scheduling strategy. In addition, the

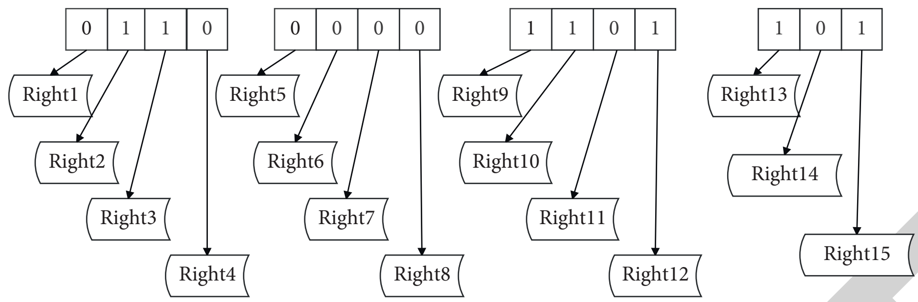

FIGURE 7: Permission logic ruler.

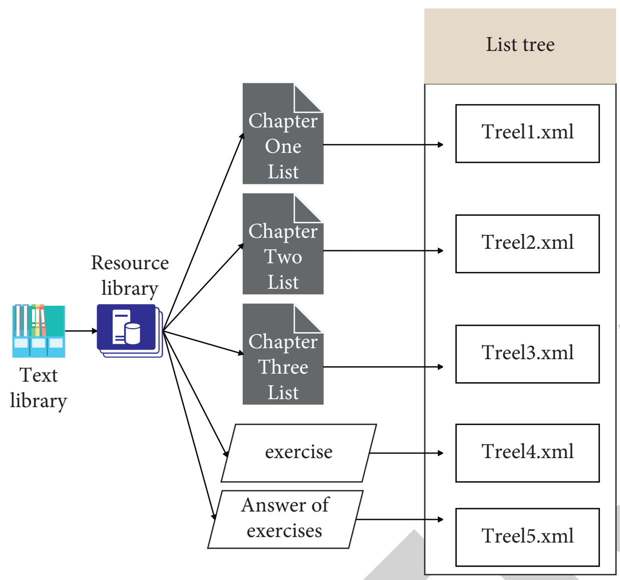

FIGURE 8: The structure diagram of the classification directory of online teaching resources for custom spoken English.

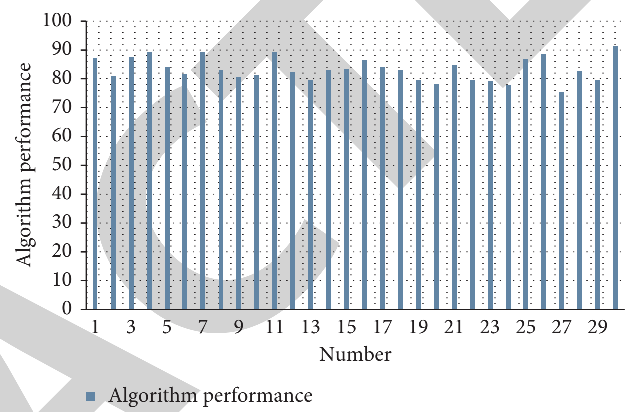

FIGURE 9: Statistical diagram of the effect of deep learning in the processing of online teaching resources of spoken English.

TABLE 1: The effect of deep learning in the processing of online teaching resources of spoken English.

Number	Algorithm performance	Number	Algorithm performance
1	87.3	16	86.4
2	81.0	17	84.0
3	87.7	18	82.9
4	89.3	19	79.6
5	84.2	20	78.2
6	81.6	21	84.8
7	89.3	22	79.5
8	83.2	23	79.1
9	80.6	24	78.0
10	81.2	25	86.7
11	89.5	26	88.6
12	82.4	27	75.3
13	79.7	28	82.8
14	82.9	29	79.5
15	83.5	30	91.3

TABLE 2: Evaluation of the online teaching resource sharing system of spoken English.

Number	Resource sharing	Number	Resource sharing
1	78.3	16	90.4
2	89.0	17	73.5
3	76.5	18	72.1
4	86.6	19	86.0
5	83.5	20	91.2
6	79.4	21	75.9
7	93.5	22	87.0
8	80.1	23	72.7
9	76.9	24	85.0
10	87.5	25	77.2
11	84.9	26	71.9
12	88.0	27	80.8
13	77.5	28	89.9
14	85.5	29	76.8
15	70.2	30	89.3

schedulability analysis under the HLC-PCP protocol also satisfies the nature of the Audsley priority setting algorithm.

The schedulability of a task τ_k is related to the set of tasks whose fixed priority is higher than it. However, it has nothing to do with the relative size of the fixed priority between tasks in the high-priority task set.

The schedulability of a task τ_k is related to the set of tasks whose fixed priority is lower than it. However, it has nothing to do with the relative size of the fixed priority between tasks in the low-priority task set.

For two tasks τ_i and τ_j, if the fixed priority of task τ_i is lower than τ_j and τ_i is schedulable, then after the fixed priorities of task τ_i and task τ_j are exchanged, task τ_i must still be schedulable.

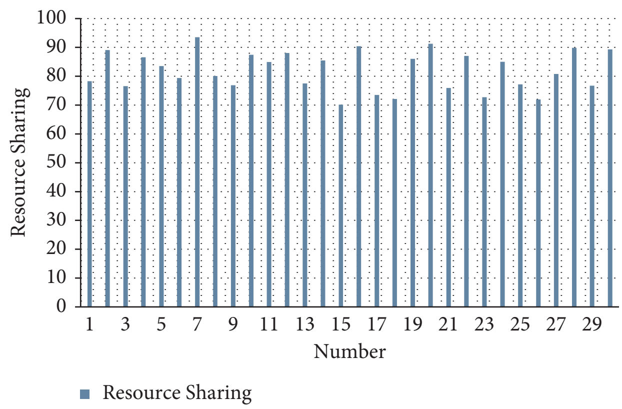

Figure 10: Statistical diagram of the evaluation of the online teaching resource sharing system of spoken English.

For two tasks τ_i and τ_j, if the fixed priority of task τ_i is higher than τ_j and τ_i is not schedulable, then after the fixed priorities of task τ_i and task τ_j are exchanged, task τ_j must still be unschedulable.

Therefore, the Audsley algorithm is suitable for priority setting under the HLC-PCP protocol.

4. Sharing of Online Teaching Resources of Spoken English Based on Deep Learning

According to the actual online teaching resources classification of spoken English, the management methods of multimedia spoken English online teaching resources and text classification management methods can effectively improve management efficiency and realize management responsibilities. The specific categories are shown in Figure 2.

The classification standard of online teaching resources of spoken English has become an important technical factor in the classification design. The data structure used by this system in this regard is more detailed and clearer, as shown in Figure 3.

According to the characteristics of the online teaching resource management platform for teaching spoken English in colleges and universities, this paper uses the database and file system to realize the storage and management of the online teaching resources of text-based spoken English and the online teaching resources of document-based spoken English. Figure 4 shows the storage structure of online teaching resources of spoken English.

As a bridge between the real and the virtual, this abstract method is more universal. The detailed E-R diagram design is shown in Figure 5.

The design interface of the network deployment module of the online teaching resource management system for spoken English in colleges and universities is shown in Figure 6.

This paper introduces the database-side custom method and the WEB server-side hierarchical display method and realizes the differentiated processing by storing a fixed custom list data table based on a custom classification in the database. Figures 7 and 8 show the classification diagrams of online teaching resources for custom spoken English.

On the basis of the above research, the model in this paper is tested and verified. Through the processing of multiple sets of online teaching resources of spoken English, the experimental design is combined with the performance of the system in this paper to verify the performance of the system, and the effect of the deep learning method in the processing of online teaching resources of spoken English is calculated, and the results are shown in Table 1 and Figure 9.

From the above research, it can be seen that deep learning has a better effect on the online teaching resource processing of spoken English. On this basis, the system resource sharing evaluation is carried out, and the results shown in Table 2 and Figure 10 are obtained.

From the above research, we can see that the sharing method of online teaching resources of spoken English based on deep learning has a good resource sharing effect.

5. Conclusion

In fact, many colleges do not have their own internal learning-oriented spoken English teaching resource sharing system, and the management of spoken English teaching resources is chaotic. Even if there is a database of spoken English teaching resources, it is only a classified management of spoken English teaching resources. In practice, it has not been effectively used, teachers and students have not really been involved, the communication between teachers and spoken English teaching is insufficient, and the connection between teachers and students is not strong. Therefore, there is an urgent need for a unique learning-oriented English oral teaching resource sharing system to change the current situation of spoken English teaching management and communication. Based on the above analysis, this paper analyzes the sharing method of online teaching resources of spoken English in combination with deep learning methods, and builds an intelligent online teaching resource sharing system to improve the follow-up English teaching effect. According to the experimental research results, the sharing method of online teaching resources of spoken English based on deep learning has a good resource sharing effect.

Data Availability

The labeled dataset used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare no competing interests.

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