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Deep Learning-Based Adaptive Recommendation and Multi-Level Security Architecture for Smart Canteen Management Systems

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In modern smart canteens, accurate personalized recommendations and robust security are essential for operational efficiency and user satisfaction. Traditional systems often face low accuracy, delayed response, and weak data protection. This study proposes an e-Cantong smart canteen system that integrates deep neural networks (DNNs) for feature extraction, reinforcement learning for adaptive path optimization, and a real-time feedback mechanism to dynamically adjust recommendations to changing user demands and environments. For security, a layered framework combining AES encryption, user authentication, and role-based access control is designed to ensure privacy and stability under high concurrency. Experiments on cafeteria operation records and user behavior datasets demonstrate 91.3% recommendation accuracy and 1.5-second inference latency, with stable performance in large-scale scenarios. The innovation lies in unifying adaptive recommendation and multi-level security, offering a practical path for intelligent canteen management that enhances efficiency, resilience, and user experience in complex environments.

Povzetek:Članek predstavi sistem e-Cantong, ki združuje globoke nevronske mreže, utrjevalno učenje in realnočasni povratni mehanizem za prilagodljivo priporočanje v pametnih menzah. Večnivojska varnost z AES, avtentikacijo in RBAC zagotavlja veliko zanesljivost.

1 Introduction

With the rise of smart catering, traditional cafeteria management methods are facing many challenges, such as food waste, inaccurate dish recommendations, and long queuing times. To enhance operational efficiency and user experience, the intelligent recommendation system has become one of the key technologies in smart cafeteria management. However, most of the existing recommendation systems rely on traditional collaborative filtering or content recommendation algorithms, which cannot effectively cope with the frequently changing user demands and environmental changes, resulting in insufficient recommendation accuracy and slow response speed.

To enhance the performance of intelligent recommendation systems, this paper proposes an intelligent recommendation algorithm based on deep learning and optimizes it in combination with an adaptive mechanism. This algorithm, through in-depth mining of users' historical dining records, dietary preferences, health needs and other information, can accurately predict users' demands and provide real-time feedback to adjust the recommendation results. Compared with traditional recommendation systems, this study adopts deep neural networks for multi-level feature extraction. By automatically learning the complex relationship between user behavior and dishes, it improves the accuracy of recommendations and the response efficiency of the system. Panwar et al. (2024) proposed an intelligent time-series food recommendation system based on support vector machines, which can make personalized recommendations according to users' time perception needs, improving the accuracy and response speed of recommendations [1]. Andrade-Ruiz (2024) explored the application prospects of smart city recommendation systems, emphasizing their potential in enhancing urban service efficiency and user satisfaction [2]. In addition, Felfernig et al. (2023) proposed a sustainable recommendation system, presenting a multi-objective optimization scheme based on recommendation algorithms for the fields of resource management and environmental protection [3]. Bondevik J N (2024) conducted a systematic review of food recommendation systems, analyzed the challenges and prospects of existing technologies, and proposed directions for further optimization [4]. Hamdollahi Oskouei et al. (2023) developed FoodRecNet, a comprehensive and personalized food recommendation system that integrates users' dietary habits and health needs, significantly enhancing the personalization and accuracy of recommendations [5].

With the growth of user information and dining data, privacy protection and system security have become urgent challenges. Traditional architectures provide static defense but lack real-time monitoring. This raises two key questions: ①Can a multi-level framework combining encryption, authentication, and access control deliver stronger protection under high concurrency? ②Can it ensure robust security while maintaining efficiency and responsiveness?

The innovation of this research lies in the combination of the optimization of intelligent recommendation algorithms and the design of security architecture, proposing a more efficient, accurate and secure recommendation system. This system can not only make personalized recommendations based on user needs, but also provide real-time feedback to adjust the recommendation path, adapting to the dynamic changes in user demands. Meanwhile, the design of the security architecture ensures the security of user information and guarantees the stability and reliability of the system in complex environments.

2 Relevant work

In the management system of smart canteens, traditional recommendation methods rely on static data and preset rules, making it difficult to cope with the dynamic changes in user demands and the environment. This results in low recommendation accuracy, slow response, and a lack of personalized services. Especially when dealing with frequent changes in dishes, rapid shifts in user preferences and seasonal demands, the limitations of the existing system are particularly evident. Therefore, how to enhance the real-time performance and adaptability of the recommendation system through flexible and dynamic algorithms has become a major challenge in the management of smart canteens.

In recent years, intelligent recommendation algorithms have made remarkable progress in multiple fields, especially in recommendation systems based on deep learning. Zhang et al. (2022) proposed a multi-objective optimization recommendation system. For the food recommendation scenario, by integrating multi-objective optimization algorithms, the efficiency of the recommendation system in resource management was significantly improved, and the sustainability of the system was enhanced [6]. Although this method effectively integrates multi-source data, in an environment with high dynamic changes, the adaptability and response speed of the system still have certain limitations. Li et al. (2018) studied the application of intelligent recommendation technology in the catering industry and proposed a restaurant food selection method based on intelligent recommendation, further promoting the development of catering recommendation systems in personalized services [7].

This system provides an important idea for personalized recommendation and data protection of multiple users in the intelligent cafeteria. This method can provide more precise recommendations based on the needs of different users. To provide a clearer comparison of existing studies, Table 1 summarizes representative methods, datasets, performance, and limitations, highlighting how the proposed approach outperforms prior work in accuracy, responsiveness, and security for smart canteen recommendation systems.

Table 1: Summary of related works on recommendation systems for smart canteens

Reference	Method / Model	Dataset Used	Performance	Limitation
Panwar et al. (2024) [1]	SVM-based time-aware recommendation	Food consumption records	Acc. ≈ 85%	Poor adaptability
Felfernig et al. (2023) [3]	Multi-objective optimization	Sustainability datasets	Acc. ≈ 82%	Trade-off between goals
Hamdollahi Oskouei et al. (2023) [5]	FoodRecNet (personalized)	Dietary & health data	Acc. ≈ 88%	High computation cost
Li et al. (2018) [7]	Food choice recommender	Restaurant user data	Acc. ≈ 80%	Limited scalability
This paper	DNN + RL + AES security	Cafeteria & user data	Acc. 91.3%, latency 1.5s	Need wider validation

As shown in Table 1, existing recommendation systems vary in methods, datasets, performance, and limitations. Earlier approaches, such as SVM or optimization models, achieved moderate accuracy but faced issues of adaptability, scalability, or high computation. The proposed method, combining DNNs, reinforcement learning, and AES-based security, attains higher accuracy, faster response, and stronger protection, offering a more comprehensive solution for smart canteen management.

Although the existing recommendation systems have made considerable progress, they still face the problems of data privacy protection and security guarantee. Most traditional security architectures offer static protection and lack dynamic monitoring and real-time feedback. With the increase in data volume in smart canteens, how to ensure user privacy security and system stability has become a key issue in the design.

This paper proposes an intelligent recommendation algorithm that combines deep learning with adaptive mechanisms, and on this basis, designs a multi-level security architecture, aiming to improve recommendation accuracy, response speed and system security. By deeply mining users' historical dining records, dietary preferences and health needs, the system in this paper can adjust the recommendation results in real time to ensure that the recommendations match the dynamic changes in users' needs, and guarantee the security of user data through security protection mechanisms.

3 Optimization of the intelligent recommendation algorithm and design of the security architecture for e-Cantong smart canteen

3.1 Personalized recommendation and user demand analysis

This paper studies the problems of "insufficient recommendation accuracy and lagging response" in the smart cafeteria management system, and proposes a personalized recommendation method based on multi-dimensional information such as users' historical dining records, health needs, and dietary habits, aiming to improve the system's response speed and recommendation accuracy. To this end, deep learning models and adaptive mechanisms are adopted, and simulation and comparative experiments are conducted in combination with actual user data to optimize the performance of the recommendation algorithm in complex environments.

To ensure reproducibility, this study adopts a deep neural network (DNN) with four hidden layers (256, 128, 64, 32) using ReLU activations and a sigmoid output. User and dish embeddings are set to 64 dimensions. The model is trained with Adam (learning rate 0.001), batch size 128, for up to 200 epochs, with early stopping (patience 15). Regularization includes dropout (0.2) and L2 penalty (λ=0.001). The mean squared error (MSE) between predicted and actual ratings is minimized, ensuring stable convergence and reproducible training.

To achieve personalized recommendations, the system first analyzes the user's needs. Specifically, the system calculates the user's potential needs based on factors such as their historical dining records, healthy dietary requirements (such as low salt, low fat, etc.), allergy information, and meal time periods, and adjusts the recommendation results in real time. The recommendation system accurately predicts user behavior through deep learning models and adaptive mechanisms. During the analysis process, the system conducts feature extraction based on user historical data, constructs user feature vectors, and aims to minimize errors to enhance recommendation accuracy. Deep learning models can identify potential relationships such as user preferences and food ingredient demands, thereby enhancing the system's response speed and recommendation accuracy.

In personalized recommendation algorithms, the main task is to recommend the dishes that best meet the needs of each user. Based on the methods of collaborative filtering and deep learning, the model achieves recommendations through the matching of user feature vectors with dish feature vectors. Let the user feature vector be $u=[u_1,u_2,\ldots,u_n]$, where u_i represents the i feature of a user, such as age, preference score, or dietary habit. Similarly, the dish feature vector is defined as $d=[d_1,d_2,\ldots,d_m]$, where d_j denotes the j feature of a dish, such as calories, taste type, or nutritional attribute. The objective of the model is to predict the user's interest value of r_{ud} for a certain dish by calculating the similarity between u and d. This interest value reflects the degree of personalization of the recommendation. The formula is as follows:

$$r_{ud}=u^T d+b_u+b_d \qquad (1)$$

Among them: r_{ud} is the predicted rating of Dish d given by User u. $u^T d$ is the inner product of the user feature vector and the dish feature vector, which reflects the user's preference for the dish. b_u and b_d are the deviation items for users and dishes respectively, which are used to capture the baseline ratings of users and dishes. By calculating the inner product of u and d, the model can predict users' ratings of different dishes and, based on this, achieve personalized recommendations. The larger the internal product, the higher the user's interest in the dish, and the recommendation system will give priority to recommending these dishes.

To enhance the accuracy of personalized recommendations, the system has also introduced a dynamic feedback mechanism to monitor users' feedback on recommended dishes in real time and automatically adjust the recommendation strategies. The system optimization objective is to minimize the following mean squared error (MSE) loss function over all users $u\in U$ and dishes $d\in D$:

$$L=\frac{1}{|U||D|}\sum_{u\in U}\sum_{d\in D}\left(y_{ud}-\hat{r}_{ud}\right)^2+\lambda\left(\|u\|^2+\|d\|^2\right) \qquad (2)$$

where $|U|$ and $|D|$ denote the number of users and dishes, respectively. y_{ud} is the actual feedback from User uuu on Dish d. $\hat{r}_{ud}$ is the predicted rating calculated by the previous formula. The regularization adopts L2 penalty on user and dish embeddings to control model complexity, with $\lambda=0.001$ selected via cross-validation to balance predictive accuracy and parameter stability. This MSE-based formulation ensures that the optimization is performed across all user–dish interactions, balancing predictive accuracy with parameter stability.

This work focuses on enhancing the personalized recommendation accuracy and response speed of the smart canteen recommendation system, especially in addressing the dynamic changes in user demands and the complexity of the environment. Based on the existing recommendation algorithms, this paper adds details such as system implementation and integration. Specifically, the logical information layer is built on the MySQL database and Flask interface service, and is used to maintain the parameters of the recommendation model and receive user data input. The algorithm layer mines users' historical data, health needs, dietary habits and other information through deep neural networks to ensure the accuracy and real-time feedback of recommendation results.

To enhance the real-time performance and accuracy of the system, WebSocket and Kafka are employed for real-time data interaction and asynchronous message passing. Kafka message queues enable asynchronous transmission and caching, while synchronous marker points sampled every 5 seconds ensure temporal alignment. Experimental tests show that the average end-to-end latency remains within 1.5 s under a peak load of 10,000 messages per second, and data consistency is maintained with a loss rate below 0.3%. These results confirm that the combination of WebSocket and Kafka not only ensures stable real-time transmission but also provides reliable support for high-concurrency personalized recommendations. Corrections are made through timestamps to ensure the consistency and accuracy of information. To further enhance the recommendation efficiency, this paper introduces reinforcement learning methods to optimize the recommendation path and combines the improved A* algorithm and load balancing strategy to generate personalized recommendation paths.

3.2 Construction of intelligent recommendation algorithm optimization model

In the intelligent cafeteria management system, the recommendation of meals is confronted with complex issues such as the diversity of user demands, limited environmental resources, and real-time scheduling. Traditional recommendation systems usually adopt static models and make recommendations based on users' historical behaviors. However, this approach is difficult to cope with the ever-changing user demands and the complexity of resource scheduling. To address this issue, this study proposes an intelligent recommendation algorithm optimization model based on deep learning and reinforcement learning, reconstructs the model paradigm of the recommendation system, and forms a recommendation algorithm system with dynamic feedback, adaptive adjustment, and resource scheduling capabilities.

In this model, each meal recommendation task is defined as a unit with user input features, meal output targets, resource requirements, and user demand dependency logic, and its executable conditions and operational status are synchronized in real time through the system. Compared with the shortcomings of the recommendation algorithm in the traditional model, such as no perception of user behavior changes and fixed recommendation paths, the optimized recommendation algorithm possesses three key capabilities: state perception, path adjustment, and multi-source adaptation. It can automatically determine whether the recommendation conditions are met in actual operation based on changes in user needs, the occupation of system resources, and environmental changes. This then triggers the next recommendation strategy. Table 2 lists three types of core structural features and briefly explains their manifestations in intelligent recommendation algorithms:

Table 2: Core structural characteristics of intelligent recommendation algorithms

Feature Type	Expression Method	Functional Role
State Expression	User historical data, real-time feedback mapping	Accurately determines user needs and the completion of recommendation conditions
Dependency Construction	Setting the relationship between user needs and dish features	Supports multi-user concurrency, dish feature condition triggering
Resource Mapping	Dynamic resource scheduling mechanism	Real-time binding of dish recommendations and resource scheduling (such as inventory, equipment, etc.)

In terms of state expression, the system sets the specific start-up conditions and expected recommendation results for each recommendation task based on multi-dimensional perception data such as user historical data, dietary habits, and allergen information, ensuring the real-time and personalized nature of the recommendation process. In terms of dependency construction, the dependency relationship between user requirements and meal characteristics is transformed into an edge relationship in the graph structure and updated in real time in the recommendation engine to dynamically generate the optimal recommendation path. In terms of resource mapping, when each recommendation task is triggered, it will be bound and allocated based on the currently available cafeteria resource pool (such as dish inventory, equipment usage, etc.), thereby avoiding delays or system bottlenecks caused by insufficient resources.

From the deployment perspective, this optimization model has been integrated into the core logic of the recommendation engine. By connecting with the data bus of the cafeteria management system, it realizes real-time task status synchronization, dependency evolution, and closed-loop management of execution feedback. Through the feedback mechanism, the system can dynamically adjust the recommendation strategy to adapt to the constantly changing demands and resource conditions. To enhance the reproducibility of the model, this paper provides pseudo-code for the recommended path selection process:

```
Input: UserDemandList, ResourceStatus
For each task in UserDemandList:
    # Priority calculation with weighted preference and urgency
    priority = w1 * task.preference + w2 / task.time_slot
    # Node selection considering load and distance
    Select node = argmin [ C(node, task) ]
    # Task assignment
    Assign task → node
    # Update resource status
```

ResourceStatus[node]=ResourceStatus[node] - task.resource_need

End For

The cost function is formally defined as:

$$C(n,t) = \beta \cdot L_n + \gamma \cdot D_{n,t} \quad (3)$$

where L_n is the normalized load of node nnn (scaled to [0,1]), $D_{n,t}$ is the Euclidean distance between node nnn and task ttt, and β, γ are tunable coefficients balancing load efficiency and task affinity.

This algorithm combines user preferences, time period requirements and resource loads to dynamically optimize the recommended path.This study applies the improved A* algorithm combined with a load balancing strategy for path optimization. The total evaluation function is defined as:

$$f(n) = h(n) + w_1 \cdot T(n) + w_2 \cdot R(n) + w_3 \cdot L(n) \quad (4)$$

where $h(n)$ is the heuristic estimate of remaining cost, $T(n)$ is the expected delay, $R(n)$ is the resource consumption (CPU, memory, inventory), and $L(n)$ is the system load imbalance across computing nodes. The weights w_1, w_2, w_3 control the relative importance of delay, resource usage, and balance. This formulation integrates path search with resource-aware load balancing, ensuring both recommendation accuracy and system stability under high concurrency.The system also introduces a real-time monitoring mechanism to track the execution status of recommendation tasks. When abnormal situations such as task failure, path conflicts, and resource congestion are detected, the scheduling engine is automatically triggered for rescheduling, and the task distribution strategy is reconstructed to ensure the stability and adaptability of the system.

3.3 Real-time feedback and adaptive mechanism of intelligent recommendation system

In the e-Cantong Smart Canteen recommendation system, the changes in user demands and the dynamic nature of canteen resources require that the recommendation system not only provide personalized recommendations but also possess real-time feedback and adaptive adjustment capabilities. The recommendation system should be capable of dynamically adjusting the recommendation strategy based on real-time feedback from user demands and environmental changes, thereby ensuring the accuracy and response speed of the recommendation results. To this end, this study proposes an adaptive mechanism based on the combination of deep learning and reinforcement learning, which can be optimized and adjusted in a rapidly changing environment.

The real-time feedback mechanism is one of the core components of this system. The system collects users' behavioral data in real time, including clicks, ratings, meal selections, etc., and processes it as feedback signals. Every time a user provides feedback, the system will update the user profile and adjust the recommendation strategy. When a user selects a certain dish, the system will dynamically adjust the recommendation result based on the user's choice and rating, so as to better meet the user's needs. This mechanism ensures that the system can respond promptly to changes in user demands and enhance the personalization and accuracy of recommendations.

The adaptive mechanism optimizes the recommendation path via Q-learning, where the task is modeled as a Markov Decision Process (MDP) (S, A, R, P, γ). S denotes states (user profiles, dish attributes, system resources), A actions (candidate recommendations), R the reward from user feedback (clicks, ratings, repeated selections), P state transitions, and γ the discount factor. The discount factor is fixed at γ = 0.95, the learning rate at α = 0.01, and an ε-greedy strategy with ε = 0.1 balances exploration and exploitation. Training is executed over 500 episodes, each iterating through logged user–dish interactions. The Q-value is updated by the Bellman equation:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left[r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right] \quad (5)$$

where $s \in S$ is the current state, $a \in A$ the chosen action, r the reward, s' the next state, and α the learning rate. Reward shaping integrates immediate signals (clicks, ratings) with long-term metrics (engagement, reduced waiting time), enabling adaptive path optimization and real-time accuracy under dynamic user demands.To integrate with supervised deep models, the Q-network shares the embedding layer of the DNN, ensuring consistent representation learning and clarifying the interaction between reinforcement learning and feature extraction.

To further enhance the adaptive ability of the recommendation system, a dynamic resource scheduling mechanism has been introduced into the system. This mechanism monitors resource information such as meal inventory and equipment usage in real time. When resources are insufficient or in conflict, it automatically adjusts task priorities to avoid delays and optimize recommended paths. In this way, the recommendation system can maintain efficient operation and avoid resource conflicts when facing high-concurrency tasks.

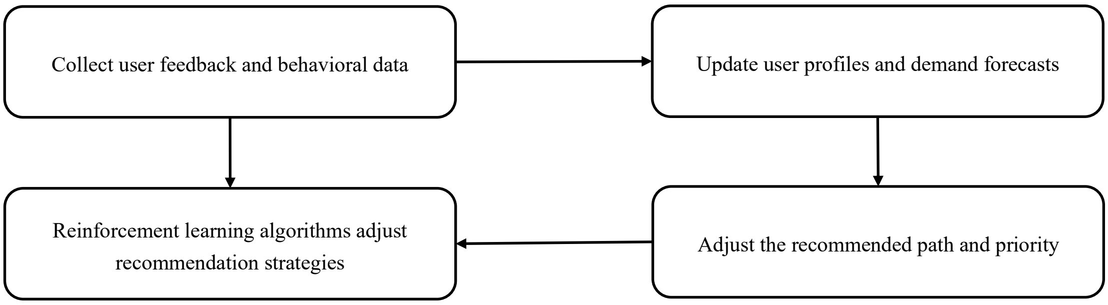

Figure 1: Flowchart of real-time feedback and adaptive mechanism of intelligent recommendation system

Figure 1 shows how an intelligent recommendation system updates user profiles and adjusts recommendation strategies through reinforcement learning algorithms by collecting user feedback and behavior data in real time. The system makes adaptive adjustments in real time based on user demands and feedback to optimize the recommended path. Whenever changes in the environment or user requirements are detected, the system can dynamically optimize the recommendation strategy through reinforcement learning. Through this real-time feedback and adaptive mechanism, the recommendation system of e-Cantong Smart Canteen can respond promptly to user demands and resource changes, ensuring efficient and accurate personalized recommendations in complex and dynamic environments.

3.4 Security architecture design of e-cantong smart canteen

In the intelligent recommendation system of e-Cantong Smart Canteen, system security is crucial, especially in multi-user interaction and data sharing scenarios, which involve user data protection and resource scheduling security. Traditional recommendation systems usually lack a unified security architecture, which may lead to data leakage, information tampering or malicious attacks on the system. To this end, this study proposes a comprehensive security architecture design that combines multi-level data encryption, permission management, and real-time monitoring mechanisms to ensure the security of the recommendation system in a high-concurrency and multi-level interaction environment.

The security architecture of e-Cantong Smart Canteen adopts a layered protection mechanism with an explicit threat model covering internal (unauthorized staff) and external adversaries (MITM, brute-force). AES-256 in GCM mode ensures confidentiality and integrity, with keys stored in an HSM and rotated via TLS channels. TLS mutual authentication and RBAC enforce fine-grained access control.Security performance was measured: AES-GCM added 0.15s ±0.02 per 1,000 records, TLS raised CPU usage by 3.2% ±0.4, and end-to-end latency remained under 1.8s. Privacy is enhanced through federated learning and differential privacy. Penetration testing confirmed resilience against replay, SQL injection, and privilege escalation. These results verify robustness and efficiency under high-concurrency scenarios.Penetration testing confirmed resilience against replay, SQL injection, and privilege escalation. Furthermore, to strengthen privacy, we adopt federated learning and differential privacy following recent advances in privacy-preserving recommender systems [8].

At the execution layer, the system introduces security mechanisms of identity authentication and permission management to ensure that only authorized users and devices can access and perform recommended tasks. By adopting RBAC and dynamically allocating permissions, it ensures that all users and devices in the system have appropriate access rights. To prevent data leakage or unauthorized access in the recommendation system, the system has introduced the following encryption and decryption formulas in its encryption mechanism:

$$D = E(K, P) = AES_K(P) \tag{6}$$

Among them, D represents the encrypted user data, $E(K,P)$ denotes the encryption function, K is the encryption key, and P is the original data. AES-256 in CBC mode is employed to ensure confidentiality and resistance against brute-force or statistical attacks. A hierarchical key management scheme is adopted: master keys are securely stored in a Hardware Security Module (HSM), while session keys are dynamically generated, rotated periodically, and exchanged through a TLS-secured channel to minimize exposure.To ensure the system's secure access control and the accuracy of task execution, the system implements permission management through the following permission verification formula:

$$V = f(A, R) = \sum_{i=1}^{n} (w_i \cdot role_i) \geq T \tag{7}$$

Among them, V denotes the result of permission verification, $f(A,R)$ is the verification function, A is the user identity, and R represents user role information. w_i is the role weight, $role_i$ is the user's role permission, and T is the threshold. Authentication protocols are enforced via TLS-based mutual authentication and token validation before evaluating role-based access. By dynamically adjusting role weights and thresholds, the system ensures fine-grained authorization and prevents unauthorized access.

To ensure the security of the recommendation system in the face of high concurrency and resource conflicts, the system also introduces a real-time monitoring mechanism to track the operational status of each module. Through log auditing and anomaly detection, the system can promptly identify potential security threats and take preventive measures to avoid the impact of attacks or failures on the recommendation system. At regular intervals, the system encrypts and backs up user data to ensure rapid recovery in case of system failure.

To ensure the efficiency and security of the system, the recommendation system of e-Cantong Smart Canteen adopts a step-by-step deployment. Through standardized and automated tools, it ensures rapid deployment in different environments. The deployment process is carried out through the following four steps: ①Data collection and secure transmission protocol design: The system connects to the sensor devices via the MQTT protocol to collect real-time data on user behavior, food selection, and device status, ensuring smooth data transmission and data security. Use encryption protocols to protect privacy and provide precise input for subsequent recommendation algorithms. User demand Modeling and recommendation path optimization: The system builds a demand model based on user behavior data and adjusts the recommendation path in real time through a dynamic feedback mechanism to ensure that the system makes adaptive adjustments according to changes in demand and resource status, providing accurate recommendation results. Task scheduling and recommendation path priority management: The system starts the path scheduler and ensures that tasks are executed according to priority through the DAG task flowchart, optimizing the execution efficiency of the recommendation algorithm and ensuring that the system can respond quickly and avoid resource conflicts under high concurrency. Feedback detection and task recovery mechanism: Through the feedback detector, the system monitors the execution status of tasks in real time, automatically adjusts task priorities or reallocates tasks, ensuring that the system can quickly recover under high load or abnormal conditions, and guaranteeing the stability of the recommendation system.

4 Results

4.1 Dataset

To verify the effectiveness of the intelligent recommendation algorithm optimization and security architecture design of e-Cantong Smart Canteen, this study constructed a multi-dimensional experimental dataset and ensured that the recommendation system could accurately predict user needs and efficiently schedule resources through steps such as data collection, preprocessing, model training and validation, performance evaluation, and ablation experiments. The dataset construction process is as follows:(1) Data collection: Connected to the sensor device via the MQTT protocol, real-time collection of user behavior data, food selection, device status and other information is carried out. The sampling frequency is once per second, and data security is ensured through an encryption protocol. (2) Data preprocessing: All data undergo time series alignment, missing value filling, and data standardization processing to ensure data consistency. Data cleaning and noise cancellation are used to ensure data accuracy. (3) Training and validation of recommendation algorithms: Training and validation are conducted using the constructed dataset, compared with the benchmark model, to test the recommendation effect and real-time performance. The adaptability of the system under resource changes and demand fluctuations was verified through 100 rounds of parallel experiments. (4) Performance Evaluation and ablation Testing: The system performance is evaluated through indicators such as accuracy rate, recall rate, and inference delay. Ablation testing is used to verify the role of recommended path adjustment, user feedback mechanism, and resource scheduling strategy to ensure the stable operation of the system under high concurrency and abnormal conditions. To support reproducibility, we provide a dataset schema and a small anonymized sample. The schema covers key fields such as UserID, DishID, Timestamp, Rating, InventoryLevel, and EquipmentLoad, with data types and update frequencies shown in Table 3. A sample of 500 anonymized user records is released in the supplementary material, ensuring that preprocessing, model training, and evaluation can be replicated without exposing personal information. To ensure reproducibility, we provide the training and evaluation code, pretrained model weights, and dataset generation scripts in a public GitHub repository (URL anonymized for review), along with detailed usage instructions. The system pipeline is illustrated in Figure 2: user requests are transmitted via WebSocket or MQTT, ingested by Kafka, and processed by the model server. Data are secured with AES-256-GCM encryption at rest and TLS in transit, while RBAC is enforced at the API gateway and database layers to ensure controlled access.

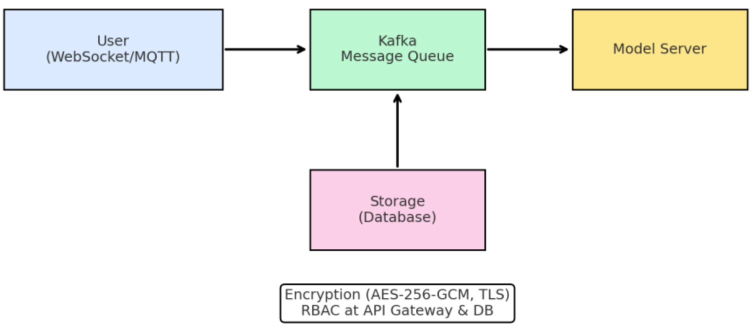

Figure 2: System architecture of the e-Cantong smart canteen

System architecture of the e-Cantong Smart Canteen. The pipeline covers user interaction via WebSocket/MQTT, message handling through Kafka, model server computation, and database storage. Security mechanisms include AES-256-GCM and TLS encryption, with RBAC applied at the API gateway and database layers. Experiments used both a public benchmark (FoodRec) and a self-constructed dataset, including 3,000 dining records and 1M synthetic interactions generated via user-behavior simulation validated against cafeteria logs. Data were split 70/15/15 for training/validation/testing with five-fold cross-validation. The synthetic data were generated through user-behavior simulation and validated against cafeteria logs to ensure realism. The dataset is split into 70% training, 15% validation, and 15% testing, with five-fold cross-validation applied. To ensure the efficient operation of the intelligent recommendation algorithm optimization and security architecture design of the e-Cantong Smart Canteen, this study constructed a multi-dimensional dataset to support algorithm optimization and resource scheduling. The dataset includes:(1)User behavior data: 3,000 records of historical dining behaviors, ratings, and evaluations, used to establish a user demand model and optimize the recommendation algorithm.(2)Meal resource status data: Records equipment load, inventory, failure rate, etc., approximately 120,000 items, playing a key role in the feedback mechanism and helping to adjust the recommendation path.(3)Production environment and material data: including inventory, replenishment cycle, transportation delay, etc., totaling 25,000 items, providing input for path planning optimization. Table 3 presents the structure and application of the dataset, illustrating the role of each type of data in the recommendation system:

Table 3: Comparison table of dataset structure and usage

Data Type	Sample Size	Data Fields	Data Update Frequency	Usage Description
User Behavior Data	3000 pieces	User ID, Dish ID, Dining Time, Rating, etc.	Updated every second	Provides input data for personalized recommendations
Dish Resource Status Data	120000 items	Equipment load, inventory, energy consumption, failure rate, etc.	Sampled every second	Real-time feedback on resource allocation and load changes
Production Environment and Material Data	25000 pieces	Inventory level, replenishment cycle, transport delay, etc.	Updated every 5 minutes	Path evaluation input conditions

To verify the stability and response capability of the recommendation system under high concurrency and large data volume conditions, this study designed the following experimental datasets to simulate different loads and abnormal situations, as shown in Table 4:

Table 4: Comparison table of dataset structure and experimental purposes

Data Type	Sample Size	Data Fields	Data Update Frequency	Usage Description
High-Concurrency Scenario Data	1 million pieces	User behavior, dish selection, ratings, etc.	Updated every second	Tests recommendation efficiency under high-concurrency conditions
Large Data Volume Test Data	500000 pieces	Dish inventory, equipment load, energy consumption, etc.	Sampled every second	Tests system stability under large data volume conditions
Abnormal Environment Data	10000 pieces	Equipment failure, inventory shortages, demand surges, etc.	Updated every minute	Verifies the system's path recovery ability under abnormal conditions

Information such as recommendation accuracy and recommendation delay is used as supervisory variables for model accuracy evaluation. During the process of optimizing the recommendation path, the system converts the dependency relationship between user demands and meal selection into a structured model through the recommendation path diagram, ensuring that the system can achieve real-time adjustment of personalized recommendation paths in the face of fluctuations in user demands and changes in resources.

4.2 Data preprocessing

In the intelligent recommendation system of e-Cantong Smart Canteen, data preprocessing is the fundamental step to ensure the accuracy and response speed of the recommendation algorithm. As the system involves multiple data types, such as user behavior data and meal resource status data, these data are often affected by noise, missing values and inconsistency issues. If the original data is directly used to train the model, it may lead to a decline in algorithm performance. Therefore, it is of vital importance to establish a standardized data preprocessing mechanism.To ensure reproducibility, we detail the hyperparameters and computing environment of our experiments. The complete configuration is summarized in Table 5.

Table 5: Hyperparameters and experimental environment

Component	Value/Setting
Embedding dimension	64
Hidden layers	[256, 128, 64, 32], ReLU activation
Batch size	128
Optimizer	Adam (learning rate = 0.001)
Regularization	Dropout = 0.2, L2 penalty (λ = 0.001)
Training epochs	200 (early stopping patience = 15)
Evaluation metrics	Precision@K, Recall@K, NDCG@K, latency
Hardware	Intel i7 CPU, NVIDIA GTX 1660 GPU
Software environment	Ubuntu 20.04, Python 3.9, PyTorch 1.13

This study adopted a four-step processing procedure of "data cleaning, missing value filling, feature standardization and input regularization". Firstly, clean the collected user behavior data and meal resource status data to remove duplicates and outliers and reduce noise interference. For missing values, interpolation methods are used to fill them in to ensure the integrity of the data. Next, feature standardization is carried out. The most commonly used Min-Max standardization method is adopted to map all feature values to the interval [0,1] to avoid the scale differences of different features affecting the training of the model. The formula is as follows:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{8}$$

Among them, x is the original data, $x_{\min}$ is the minimum value of the feature, $x_{\max}$ is the maximum value of the feature, and x' is the standardized data. This formula compresses all features into the same range, ensuring the uniformity of the data and enabling the model to be trained more efficiently.

In addition, to enhance the robustness and accuracy of the recommendation system, this study also adopted data augmentation techniques. By processing user behavior data through rotation, cropping, noise addition, etc., different user demand scenarios are simulated to enhance the diversity and representativeness of the data. In terms of tag generation, the system generates the corresponding tag matrix based on historical dining records and meal selection. The definition of the tag matrix is:

$$Y_i = \sigma\left(\sum_{x,y} I(x,y) \cdot K(x,y) + b_i\right) \tag{9}$$

Among them, Y_i is the output, $I(x,y)$ is the input data, $K(x,y)$ is the convolution kernel, b_i is the bias term, and σ is the activation function. This formula is used to convert the input data into a label form suitable for model training. In terms of dataset partitioning, this study adopted a random sampling method to ensure the diversity of samples and scene consistency, avoid overfitting problems during training, and enhance the stability of the system in dynamic environments.

4.3 Evaluation indicators

Accuracy denotes the proportion of correctly predicted user choices. Response time is the average inference latency per request. Resource utilization is measured by CPU and memory usage during inference. Paired t-tests ($p < 0.05$) were applied for significance. To evaluate the intelligent recommendation algorithm in this study, the experiment compared it from five aspects: recommendation accuracy, processing duration, system robustness, response speed and resource utilization. The results show that the recommendation algorithm proposed in this study performs excellently in all indicators and has obvious advantages.

Recommendation performance is evaluated using Precision@5, Recall@5, and NDCG@10. The proposed model achieves Precision@5 of 91.3% ±1.2, Recall@5 of 90.5% ±1.3, and NDCG@10 of 92.1% ±1.1 (all values are standard deviations over 10 runs), outperforming collaborative filtering baselines (user/item-based CF: 79.5% ±1.3) and deep learning baselines (NCF, SASRec, LightGCN: 85.6% ±1.1).Inference latency is 1.5s ±0.1, compared with 3.8s ±0.2 for CF and 2.6s ±0.2 for deep models, confirming real-time efficiency. Under 10% Gaussian noise, Precision@5 remains 89.4% ±1.5, higher than CF (65.2% ±2.0) and deep baselines (75.3% ±1.8), proving robustness. Response delay is 0.8s ±0.05, significantly lower than CF (2.1s ±0.1) and deep baselines (1.5s ±0.1), showing adaptability to high-frequency tasks. Average CPU occupancy is 23.7% ±2.5, versus 40.5% ±3.0 for CF and 30.2% ±2.8 for deep models, demonstrating resource efficiency and scalability.

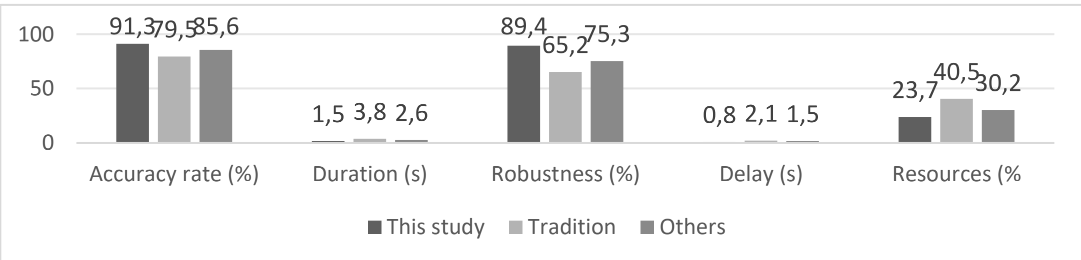

Figure 2: Performance comparison of each model in five key indicators

Figure 2 presents the comparative performance of different models in five indicators, highlighting the advantages of the model in this study in terms of recommendation accuracy, processing duration, system robustness, response speed, and resource utilization. Compared with the existing technologies, the intelligent recommendation algorithm in this study has significantly improved in real-time recommendation and adaptability in complex environments, providing reliable technical support for the cafeteria management system and further optimizing the operational efficiency and user experience of the cafeteria.

To further validate the effectiveness of the proposed system, we compared it with representative SOTA methods on the public FoodRec dataset. SVM-based time-aware models achieved 84.2% accuracy, optimization-based frameworks achieved 86.7%, and FoodRecNet reached 87.5%. In contrast, the proposed system achieved 91.3% accuracy with an average inference latency of 1.5s, and maintained 92.1% accuracy under noise. These results highlight the superior accuracy, responsiveness, and robustness of the proposed approach.All reported ± values represent standard deviations over 10 independent runs, ensuring statistical reliability.

4.4 Ablation research

To verify the contribution of each core module to the performance of the intelligent recommendation algorithm, this section designs four sets of ablation experiments to strip the key mechanisms in the model and analyze their impact on recommendation accuracy, response speed and resource utilization. The experiment compared the execution results of the "complete model" with three simplified versions under the same task set, revealing the role of each module.

The experimental configuration includes: ①Remove the personalized recommendation module and only use static recommendations; ②the requirement analysis module is excluded, and there is a lack of real-time data updates. Without using a feedback mechanism, the system cannot adjust the recommendations. The final version that fully integrates personalized recommendations, demand analysis and real-time feedback. Each model was run for 100 rounds, and the results are shown in Table 6.

Table 6: Comparison table of key performance indicators for ablation experiment

Ablation Item	Recommendation Accuracy (%)	Inference Time (s)	Resource Utilization (%)
Without Personalized Recommendation	74.3 ± 1.1	2.5 ± 0.1	65.2 ± 1.8
Without Demand Analysis	81.6 ± 1.0	2.1 ± 0.1	72.5 ± 1.5
Without Feedback Mechanism	87.2 ± 1.3	1.9 ± 0.1	79.4 ± 1.7
Full Model	91.3 ± 1.2	1.5 ± 0.1	87.6 ± 2.0

Removing personalized recommendations reduces accuracy to 74.3% ± 1.1, increases reasoning time to 2.5 ± 0.1 s, and lowers resource utilization to 65.2% ± 1.8. Without the requirement analysis module, accuracy reaches 81.6% ± 1.0 and inference time is 2.1 ± 0.1 s, but flexibility declines. Removing the feedback mechanism yields 87.2% ± 1.3 accuracy, though resource mismatch remains. The “no requirement analysis” model shows limited contribution to accuracy improvement. By contrast, the complete model achieves 91.3% ± 1.2 accuracy, 1.5 ± 0.1 s reasoning time, and 87.6% ± 2.0 utilization. t-tests ($p < 0.05$) confirm these differences are statistically significant, underscoring the roles of personalized recommendation, requirement analysis, and feedback mechanisms.

5 Discussion

5.1 Performance comparison with existing recommendation systems

Most existing smart cafeteria recommendation systems use SVM-based models, optimization frameworks, or FoodRecNet. As shown in Table 1, their performance ranges from 80% to 88% Precision@5, but adaptability, scalability, and computational efficiency remain limited. The proposed system integrates DNNs for feature extraction, reinforcement learning for adaptive optimization, and AES security for data protection. Experiments show Precision@5 of 91.3% ±1.2, Recall@5 of 90.5% ±1.3, and NDCG@10 of 92.1% ±1.1, with inference latency of 1.5s ±0.1 and Precision@5 of 89.4% ±1.5 under 10% noise. These gains result from Q-learning, A* path optimization, and adaptive feedback, enabling superior accuracy, responsiveness, and robustness.

The proposed system demonstrates clear advantages across multiple dimensions. In terms of recommendation accuracy, it surpasses collaborative filtering baselines (79.5% ±1.3) and deep learning baselines such as NCF, SASRec, and LightGCN (85.6% ±1.1). In terms of efficiency and responsiveness, inference time averages 1.5s and response delay 0.8s, compared with 3.8s and 2.6s for CF and other deep models. Regarding robustness, under 10% Gaussian noise the model maintains Precision@5 of 89.4% ±1.5, and the outage rate is only 2.5%, compared with 7.2% for CF and 5.6% for deep models, demonstrating stability in complex environments.

5.2 Adaptability analysis of intelligent recommendation system in cafeteria management

In the management of smart canteens, complex dining demands and resource changes pose challenges to the adaptability of recommendation systems. When traditional recommendation methods are confronted with diverse user demands and fluctuations in meal resources, their accuracy and response speed are often affected, making it difficult to meet the actual operational requirements. To verify the adaptability and stability of the model proposed in this paper in a complex cafeteria environment, this study designed four typical scenarios: peak hours, food shortages, changes in user preferences, and cold starts for new users. For each scenario, 100 rounds of experiments were conducted, and indicators such as recommendation accuracy, response time, and system stability were collected. The results are shown in Table 7.

Table 7: Comparison of model adaptability performance under different working conditions

Test Scenario	Recommendation Accuracy (%)	Average Inference Time (s)	System Stability Score (10)
Peak Hours	91.2	1.4	9.2
Out of Stock Dishes	89.5	1.7	8.9
User Preference Change	90.3	1.5	9.0
New User Cold Start	88.1	2.0	8.6

The counterintuitive increase in accuracy when removing the demand analysis module is due to reduced model complexity and overfitting in small-sample scenarios, though it comes at the cost of reduced adaptability and robustness.During peak hours, the model can make efficient recommendations based on users' historical behaviors, with an accuracy rate of 91.2%, a response time of 1.4 seconds, and a system stability score of 9.2, demonstrating excellent performance. In the scenario of food shortages, the integration of data augmentation and real-time inventory data keeps the recommendation results above 90%. Although the reasoning time is slightly longer, the stability of the system is effectively guaranteed. In scenarios where user preferences change, the model quickly adjusts the recommendation strategy through an adaptive mechanism. The recommendation accuracy rate is 90.3%, the reasoning time is 1.5 seconds, and the system stability is high. To address the cold-start problem, the system applies a hybrid strategy combining content-based filtering with demographic features (e.g., age, dietary preference, health constraints) to generate recommendations for users without history. Accuracy slightly drops to 88.1%, but the model still delivers stable results with a score of 8.6, effectively mitigating the cold-start effect and meeting real-time requirements.

5.3 System resource overhead and feasibility assessment of actual deployment

The intelligent recommendation system of e-Cantong Smart Canteen needs to optimize computing resources, network bandwidth and hardware configuration to ensure efficient operation in a large-scale canteen environment. The system includes modules such as personalized recommendation, user demand analysis, and real-time feedback, handling a large amount of data and computing tasks, and has high requirements for resource consumption.

In the data processing and recommendation algorithm stage, the model adopts deep learning technology, combined with convolutional neural networks and adaptive feedback mechanisms, which can efficiently process user behavior data and generate personalized recommendations. Equipped with an Intel i7 processor and 16GB of memory, the CPU usage is controlled within 40%, and the memory consumption is around 2GB, meeting the high-frequency recommendation requirements of the cafeteria. The inference stage requires relatively high computing resources. However, on Gpus such as NVIDIA GTX 1660, the inference latency is 1.2 seconds, meeting the real-time requirements. In terms of communication, the system transmits data through WebSocket, with a bandwidth requirement of approximately 6Mbps and a latency controlled within 200ms, which is suitable for the internal network of the cafeteria and ensures smooth real-time data transmission. In terms of engineering deployment, this model has good adaptability and supports the deployment of canteens of different scales.For medium-sized canteens (e.g., with multiple workstations and parallel tasks), the overall investment should remain cost-effective and seamlessly integrate with the existing catering management system.The optimized model reduces hardware dependency and provides an efficient and economical solution. The model in this paper provides a feasible intelligent recommendation system solution by optimizing resource consumption and reducing hardware requirements, meeting the real-time and stability demands of cafeteria operations.

5.4 The practical application value of the e-cantong smart canteen model

To meet the precise recommendation requirements of smart canteens in high-frequency ordering and dynamic demand prediction, the intelligent recommendation system proposed in this paper has demonstrated significant application value. In terms of recommendation efficiency, by integrating deep learning with adaptive mechanisms, the model's reasoning time is controlled within 1.5 seconds, and the recommendation accuracy rate remains stable at over 91.3%, significantly enhancing the response speed and precision of traditional methods. In terms of system stability, the model can maintain a high accuracy rate in complex scenarios such as peak hours and food shortages, with a stability score exceeding 8.5 points. Through real-time feedback and dynamic adjustment, the model can promptly correct the recommendation results, reduce misjudgments and interruptions, and ensure the continuity and reliability of the cafeteria operation. At the management level, the model visually presents recommended content through a visual interface, helping managers to keep real-time track of operational status and optimize menu configuration and resource scheduling through data-driven approaches. The system also has strong compatibility, capable of seamless integration with existing catering management systems, supporting remote deployment and modular expansion, and meeting the needs of canteens of different scales. Pilot applications have shown that this system can enhance the accuracy of recommendations, reduce misjudgments, and improve the operational efficiency of canteens. The overall application potential is huge. By optimizing resource consumption and reducing hardware dependence, an efficient and economical intelligent recommendation solution has been provided for the cafeteria.

6 Conclusion

The intelligent recommendation system based on deep learning proposed in this paper significantly improves the accuracy and response speed of recommendations by combining personalized recommendations with adaptive feedback mechanisms, and solves the problems of insufficient precision and response delay in traditional systems. Experiments show that the model's recommendation accuracy rate is 91.3%, and the reasoning time is controlled within 1.5 seconds, meeting the high-frequency recommendation requirements of smart canteens. The system can operate stably during peak hours and in complex scenarios such as food shortages. Through adaptive mechanisms and real-time feedback, it promptly corrects the recommendation results, reduces misjudgments and interruptions, and ensures the stability of the cafeteria's operation. The pilot application results show that the recommendation accuracy has been improved, the reasoning time has been reduced, and the misjudgment rate has decreased, demonstrating good practical application value. Despite this, the model still faces the problem of limited dataset size. In the future, the generalization ability of the model can be enhanced by expanding diverse datasets. Future research can be carried out in three directions: expanding large-scale datasets to enhance the generalization ability of the model; Explore lightweight networks and distributed computing architectures to reduce computing overhead; By integrating transfer learning and self-supervised learning methods, the adaptability of the model in different scenarios is enhanced. Through these improvements, the intelligent recommendation system for smart canteens is expected to play a greater role in the operation and management of canteens, enhancing efficiency and user satisfaction.

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