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Intelligent Scientific Cabinet System Based on Large-Scale Language Model And RFID Technology

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***Abstract*—This study proposes an intelligent scientific cabinet system that integrates large language models and radio frequency identification (RFID) technology, aiming to enhance the management efficiency and safety of hazardous chemicals. Current traditional hazardous chemical storage cabinets, such as Ronghai Tongda and Sanling Hazardous Chemical Intelligent Storage Cabinets, lack real-time monitoring and intelligent early warning mechanisms, making it difficult to adapt to complex safety standards and regulatory requirements. This system achieves closed-loop management of hazardous chemicals throughout their entire lifecycle through real-time monitoring, data analysis, behavior analysis, and environmental monitoring. The hardware part uses a carbon steel spray-painted shell, integrated with an Android industrial host and RFID reading and writing device. The software architecture combines LLM with RFID technology, integrating information at the terminal, and through prompt engineering and retrieval enhancement generation, it achieves precise management and information generation. Experimental results show that the system can effectively improve management efficiency, ensure compliance, and enhance safety.**

Keywords-Retrieval Enhancement; Large Language Models; Radio Frequency Identification; Prompt Engineering; Full Lifecycle Management

I. Introduction

In recent years, numerous laboratory accidents involving hazardous chemicals, such as chemical plant explosions and biological laboratory leaks, have highlighted the deficiencies in current management methods. These incidents not only result in casualties and economic losses but also severely affect the normal operation of scientific research projects. Therefore, there is an urgent need for a more efficient and intelligent solution [1].

Although traditional hazardous chemical storage solutions, such as Ronghai Tongda and Sanling Hazardous Chemical Intelligent Storage Cabinets, provide basic physical protection and safety features, they generally lack real-time monitoring and intelligent early warning mechanisms, making it difficult to adapt to complex safety standards and compliance requirements. Moreover, RFID technology [2] has significant advantages in item tracking, but when used alone, it suffers from insufficient data analysis and limited intelligent management capabilities [3]. These limitations make existing management systems ineffective in preventing and responding to potential safety risks [4].

Functional aspect,our system integrates large language modelsand RFID technology, enabling real-time monitoring, data analysis, behavior analysis, environmental monitoring, and intelligent recommendations throughout the entire lifecycle of hazardous chemicals. In contrast, other systems may only offer basic storage and limited monitoring capabilities. In cost:,while some advanced intelligent storage systems may have higher upfront costs, our system provides a cost-effective solution without compromising on features. The integration of Large Language Models (LLM) and RFID technology allows for efficient management without the need for expensive additional hardware, all need is a screen with a simple development board.

This study proposes an intelligent scientific cabinet system that integrates LLMand Radio Frequency Identification (RFID) technology. The system achieves closed-loop management of hazardous chemicals throughout their entire lifecycle through real-time monitoring, data analysis, behavior monitoring, and intelligent recommendations [5].

II. System Design and Architecture

In terms of system design and architecture(Figure 1)[6], the hardware of this system features a carbon steel spray-painted enclosure, built-in Android industrial host, and advanced RFID reading and writing equipment [7]. It includes

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the functions of a traditional storage cabinet (VOC, temperature, and humidity sensors) as well as a return station with a weighing system (Table 1). On the software side, the intelligent analysis capabilities of the LLM are enhanced through the Retrieval-Augmented Generation (RAG) framework and a professional knowledge base, enabling real-time monitoring, behavior analysis, environmental monitoring, and intelligent recommendations for hazardous chemicals, covering every stage from procurement to disposal. Additionally, it integrates temperature and humidity monitoring and safety alarm mechanisms [8] as well as timely emergency response plans.

TABLE I. HARDWARE PARAMETER TABLE

Components	Parameters	Description
Housing material	Carbon steel painting	Corrosion resistance, strength
Size	1100mm-620mm-1900mm	Maximize storage
Power	200VAC(±10%),50±3HZ	Power supply
RFID	E710 chip(read rate 3-5 seconds)	High-speed reading
Display Screen	10-inch(1280×800)	Operation interface
Temperature and humidity adaptation range	-20°C to 60°C, 20%-85% humidity	Laboratory environmental needs
Data Collection Frequency	Every minute	Data collection frequency
Response Time	10-25 seconds	The time it takes for the system to respond after data is collected
False Alarm Rate	The rate at which false alarms are triggered	False alarm rate: <5%

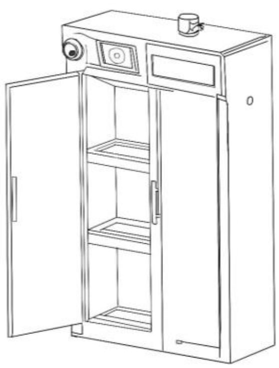

Figure 1. Intelligent scientific research cabinet

To use RFID in this metallic environment htigh frequency (HF) RFID tags are used, operating at 13.56MHz. These tags have better resistance to metal interference, have shorter wavelengths, and are better able to penetrate metal surfaces. And an antenna is installed on the side of the storage cabinet to cover the chemical containers at different locations in the cabinet. Make sure that containers can be read from different angles.

III. CORE FUNCTIONS AND INNOVATIVE APPLICATIONS

The core functions of the intelligent scientific cabinet system are centered around the precision and safety of hazardous chemical management. The system implements real-time monitoring, tracking the exact location and status of hazardous chemicals through RFID technology to ensure the accuracy of inventory. The behavior analysis module uses the Large Language Model (LLM) to analyze operation logs, detect non-compliant behaviors, and trigger early warnings [9]. The environmental monitoring module continuously monitors environmental parameters such as temperature and humidity, and automatically triggers alarms when preset thresholds are exceeded, maintaining the suitability of the storage environment. The intelligent recommendation module analyzes historical usage data to provide optimized suggestions for the use of materials, thereby improving experimental efficiency.

IV. SYSTEM IMPLEMENTATION AND EXPERIMENTS

A. *Specialized Training*

The implementation of the Large LanSpecialized Traininggguage Model (LLM) within the intelligent scientific cabinet system is crucial [10]. The system utilizes the GLM4V:9B from Zhipu AI as an offline multimodal model (with the option to use the online GLM-4V) as the base model, which involves three modules. First, the Retrieval-Augmented Generation (RAG) is employed to construct a vector database (LanceDB) that stores pre-processed professional knowledge documents selected from various fields . When a user queries, the LLM converts the user input into a query through text embedding (OpenAI Embedder), matches it with vectors in the vector database, retrieves relevant professional content, and dynamically generates customized safety recommendations and operation optimization reports (Figure 2).

Following through with parameter fine-tuning (Fine-Tuning), where LoRa is a fine-tuning technique that can adjust the model by adding a low-rank matrix to the existing weight matrix. This can effectively adjust the model with a minimal increase in computational burden. The LoRa technique is used to fine-tune the GLM4, employing a standardized dataset from the field of hazardous chemical management (Figure 3) to retrain the LLM, This example Chinese text is used to fine-tune the large language model in QA format to provide safety recommendations and operational optimization reports for storing flammable liquids (acetone),enabling it to handle specific tasks more accurately.

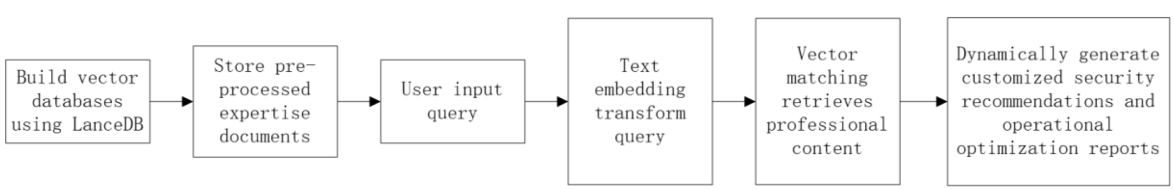

Figure 2. Implementation of LLM specialization

```
{
  "messages": [
    {
      "role": "system",
      "content": "You are a professional hazardous chemicals management AI assistant, focusing on providing safety recommendations
       operational optimization reports."
    },
    {
      "role": "user",
      "content": "I need to store a batch of flammable liquids, such as acetone. What safety precautions should I take?"
    },
    {
      "role": "assistant",
      "content": "When storing flammable liquids like acetone, the following safety precautions must be observed:\n1. Ensure that
      storage areas are away from fire sources and hot areas to prevent accidental ignition.\n2. Acetone should be stored in a fl
      ame-resistant cabinet, and the cabinet must be grounded to prevent the accumulation of static electricity.\n3.  The storage
      area should be equipped with appropriate fire-fighting equipment, such as foam extinguishersand dry powder extinguishers.4.
      Ensure that containers are properly sealed to prevent leakage.\n5. The storage area should have adequate ventilation to red
      uce the risk of accumulation of flammable gases.\n6. Follow hazard labeling guidelines to ensure all containers are properl
      y marked.\n7. Conduct regular safety inspections to ensure storage conditions meet regulations.\n8."
    }
  ]
}
```


Figure 3. Fine-tuning example data

LangChain technology equips the system with the capability to handle multi-step tasks. It automates the processing of data streams, ensuring that inputs, after pre-processing, can be directly passed to the model for inference. The context management capability allows the model to provide a dynamically updated context window, enabling the model to continuously access and apply key background information in complex tasks. LangChain's Tool Integration integrates external APIs or databases with the model, invoking external resources during the inference process to enrich the model's responses [11][12]. Through its task decomposition (Agent) feature, it breaks down complex problems into multiple steps, which are processed individually by the LLM and integrated step by step. Based on this approach, a processing chain for various functions is established, enhancing the system's long-term intelligent processing capability for hazardous chemical management[13].

B. *Real-time Monitoring and Data Analysis Reporting*

By installing readers within the scientific cabinet that emit radio waves at specific frequencies, the transponders in the hazardous chemical tags are activated. The tags on the hazardous chemicals then reflect back information carrying the unique identifiers of the items, which are captured by the reader and transmitted in real-time to the central database to retrieve various information about the corresponding items. Concurrently, location and temperature and humidity data are captured, images are taken and transmitted, and these data are combined with prompt words from specific stages to form a new query parameter. This parameter is queried in the LLM's vector database to retrieve relevant management standards and historical cases. The LLM analyzes the information and generates customized analysis reports for each management stage. Each stage's report serves as the input for the next stage, inheriting data from the previous stage and adding new monitoring results. The system manages every stage of hazardous chemicals, from inventory, procurement, storage, checkout, transfer, use, return to disposal, generating detailed reports that enhance management efficiency, ensure compliance, and improve the management of hazardous chemicals (Figure 4). LLM is used for a variety of applications, including using sql commands to query from the database and providing more critical information for content suggestions. LLM detection and warning are triggered when the behavior is abnormal. Collect reports issued by OSHA, EPA, CSB and other agencies, as well as professional books such as *Hazardous Chemical Storage and Handling* to fine-tune data to optimize model performance.

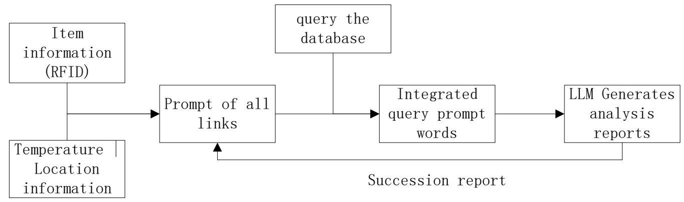

Figure 4. Real-time monitoring engineering drawing

C. *Behavior Analysis and Alarm*

Similarly, real-time data on the weight, location, and environmental conditions of hazardous chemicals, as well as the identity and time of the operating personnel, are collected. These data, after pre-processing and prompt word engineering adjustments, are input into the LLM. Based on the vector database and historical reports of abnormal behavior, the LLM utilizes natural language processing technology for in-depth analysis. It analyzes normal behavior patterns and detects anomalies, generating a behavior report for each instance of use (Figure 5). If suspicious behavior is detected, the system triggers an alarm, notifying safety management personnel to review the behavior report, conduct machine warnings, and intervene manually. Additionally, the behavior report is incorporated into the abnormal behavior vector database. Meanwhile, when environmental anomalies reach a threshold (set according to different scenario environments, as shown in Table 2), the same process is initiated (excluding the acquisition of operating user data).

TABLE II. ALARM OPERATIONS

alarm level	Threshold	operation
Level 1 alarm	Temperature/humidity slightly exceeded 5%	Prompt check
Level 2 alarm	The exceeding limit is 10% greater	Trigger operation limit
Level 3 alarm	Severe abnormalities 15%	Lock the scientific research cabinet notify safety officer

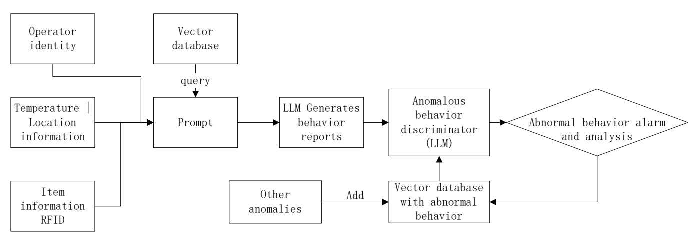

Figure 5. Behavior detection alarm flow chart

V. SYSTEM EXPERIMENTS

The objective of the experimental section is to evaluate and compare the performance of commonly used Large Language Models(Figure 6). The system employs GLM-4-Plus to simulate experimental anomalies for LLM analysis, focusing on two key performance metrics: response time and accuracy.1) Assessment of Response Time: The response time is measured by invoking the API interfaces of various models, simulating an experimental network environment, and recording the time interval from the request being sent to the complete reception of the response. Timestamps are captured, and the tests are repeated 10 times to reduce random errors, ultimately calculating the average response time.2) Assessment of Accuracy: The accuracy test is conducted by simulating experimental anomalies and manually reviewing the analysis reports generated by the models. The content of the reports is scrutinized in detail, with unclear lines identified and marked. Accuracy is quantified by the ratio of unclear lines to the total number of lines, thereby providing an objective measure of accuracy.

$$Accuracy = 1 - \frac{Number\ of\ ambiguous\ lines}{Total\ number\ of\ lines} \tag{1}$$

The analysis of the experimental results indicates that Doubao-pro-4k demonstrated the best performance in terms of average accuracy, reaching up to 94.713%. GLM-4-Plus from Zhipu AI had the shortest average response time, at 15.56 seconds. Although ERNIE4.0-turbo-8k had a slightly lower accuracy, it had the longest response time, at 17.05 seconds. Taking both factors into consideration, Doubao-pro-4k is suitable for scenarios that demand high accuracy, while GLM-4-Plus is more appropriate for applications requiring rapid response times. ERNIE4.0-turbo-8k does not excel in either speed or accuracy, and may not be suitable for scenarios with high requirements for both of these metrics (Table 3).

TABLE III. EXPERIMENTAL RESULTS

Indicators	GLM-4-Plus (this system)	Doubao-pro-4k	Ernie4.0-turbo-8k
Average accuracy	93.113%	94.713%	92.523%
Average corresponding time(s)	15.56	16.72	17.05

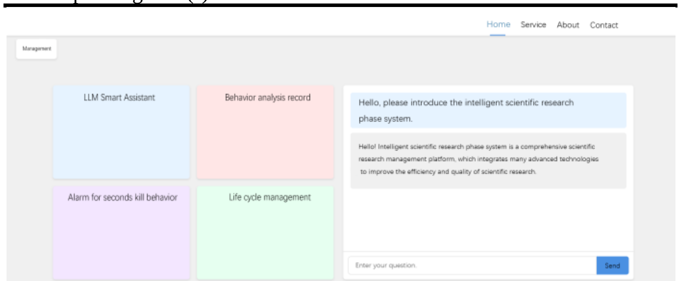

Figure 6. Experimental system

VI. CONCLUSION

The study proposes an intelligent scientific cabinet that integrates LLM and RFID technology, enhancing the management efficiency and safety of hazardous chemicals. By employing real-time monitoring, data analysis, behavior analysis, environmental monitoring, and intelligent recommendations, the system achieves closed-loop management throughout the entire lifecycle of hazardous chemicals. Compared to existing technologies, this system excels in real-time monitoring analysis, early warning of abnormal behavior, improving management efficiency across the lifecycle, ensuring compliance, and enhancing safety. Although significant achievements have been made, further research and optimization are required to assess the system's application effects in diverse scientific research environments and its adaptability to new technologies, as well as to add more functionalities. Future work will focus on updating system functionalities, optimizing LLMs, and customized training to ensure that the system continues to provide practical services in the rapidly evolving field of scientific research.

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