Deep Learning-Based Grain Depot Fire Safety Early Warning IoT System: A CSITP Practice Under Industry-Education Integration

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Abstract. Industry-education integration represents the core direction of higher engineering education reform in the new era. As a key carrier connecting classroom teaching with industrial practice, the College Students' Innovation Training Project (CSITP) serves as an important platform for cultivating interdisciplinary engineering innovation talents. To address the prominent “industry-education disconnect” problems commonly observed in current CSITP implementation—including topics detached from real industrial needs, weak hands-on training components, and limited educational outcomes—this paper takes the CSITP “Grain Depot Fire Safety Early Warning IoT System Based on Deep Learning” as the research object to explore implementation pathways and models for engineering CSITP under the guidance of industry-education integration. By deeply aligning the project with China's national food security strategy and the practical pain points of fire safety management in the grain depot industry, a full-chain practice system of “industrial demand—scheme design—system development—on-site verification—achievement transformation” is constructed. Through approaches such as collaborative guidance by school-enterprise dual mentors, phased task-driven implementation, and blended teaching combining virtual simulation with physical practice, the team completed the development of a grain depot fire safety early warning system integrating multi-source perception, intelligent recognition, PID precise control, and remote linkage. The results demonstrate that this implementation model not only effectively addresses practical industrial challenges in grain depot fire safety, but also significantly enhances students' engineering practice capabilities, innovative thinking, and team collaboration competencies, providing a replicable and scalable practical case and theoretical reference for industry-education integration in similar engineering CSITPs.

Keywords: Industry-Education Integration; College Students' Innovation Training Project; Grain Depot Fire Safety; Deep Learning; PID Control

1. Introduction

With the in-depth implementation of the national industry-education integration strategy, the policy document Several Opinions on Deepening Industry-Education Integration explicitly calls for promoting deep integration between higher education and industrial development, strengthening practical teaching components, and cultivating high-quality technical and skilled talents adapted to industrial upgrading [1]. As a core component of the Ministry of Education's “Undergraduate Teaching Quality and Teaching Reform Project for Higher Education Institutions,” the College Students' Innovation Training Project (CSITP) serves as a key platform connecting theoretical instruction with engineering practice and cultivating students' innovative spirit and practical abilities. It also represents a critical mechanism for realizing industry-education integration and school-enterprise collaborative talent cultivation [3].

However, in the implementation of CSITPs in engineering disciplines at Chinese universities, the prominent “industry-education disconnect” problem persists. First, topic selection is biased: most projects are designed primarily by faculty, lacking systematic investigation of and deep alignment with real industrial needs, which leaves project outcomes largely confined to laboratory simulation and difficult to translate into industrial applications. Second, hands-on training is weak: student

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involvement focuses largely on theoretical design and code development, with limited exposure to authentic engineering scenarios, resulting in only modest gains in engineering practice ability. Third, the mentoring system is monolithic: enterprise mentors participate insufficiently, while on-campus advisors often lack first-line engineering experience, making it difficult to provide industry-standard professional technical guidance [4,5]. These issues not only constrain the educational value of CSITPs, but also create a clear mismatch between graduates' capabilities and enterprise needs, hindering adaptation to industrial transformation and upgrading.

Food security is a vital cornerstone of national security. As the core hub for grain reserve and transit, fire safety in grain depots directly relates to the stability of national grain reserves and overall economic and social stability [10]. China maintains massive grain reserve volumes, and grain depot buildings typically feature large-span, large-volume structures storing flammable grain materials. Once a fire occurs, it spreads rapidly and is difficult to extinguish, often causing major economic losses and social impact [2]. Statistics indicate that over a hundred grain depot fire incidents have occurred in China during the past decade, with direct economic losses reaching billions of yuan. Traditional fire safety management of grain depots relies primarily on manual inspection together with simple smoke and temperature sensors, which suffers from prominent pain points including delayed warning response, high false-alarm rates, coarse-grained control, and low informatization—failing to meet the practical demands of modern grain depot safety management.

On this basis, this paper takes the national-level CSITP “Grain Depot Fire Safety Early Warning IoT System Based on Deep Learning” as the research vehicle. By deeply aligning with the practical needs of fire safety management in the grain depot industry, the study explores a full-process implementation model for engineering CSITPs under the guidance of industry-education integration. Through school-enterprise collaboration, task-driven implementation, and the integration of virtual and physical practice, the project achieves bidirectional empowerment between technical R&D and talent cultivation. It effectively addresses real industrial problems while enhancing students' engineering innovation capabilities, providing a replicable and scalable practical case for similar engineering CSITPs and supporting the in-depth advancement of higher engineering education reform.

2. Connotation and Implementation Framework of CSITP under Industry-Education Integration

2.1 Core Connotation of CSITP under Industry-Education Integration

The CSITP under industry-education integration is fundamentally about breaking down barriers between universities and enterprises. Guided by real industrial needs, it integrates industrial elements, industry standards, and engineering practice experience throughout the entire project lifecycle—topic selection, scheme design, implementation, and evaluation—to achieve deep integration of “industry” and “education” and collaborative talent cultivation. Its core connotation is reflected in three dimensions:

First, demand orientation: project topics must originate from genuine industrial pain points, with research content closely aligned with industry development trends, ensuring that outcomes possess practical application value and industrialization potential while avoiding “paper plans.” Second, collaborative talent cultivation: a robust school-enterprise dual-mentor mechanism should be established to fully leverage the theoretical strengths of on-campus advisors and the engineering practice strengths of enterprise mentors, jointly guiding students through project R&D to organically integrate theoretical knowledge with engineering practice. Third, capability orientation: emphasis is placed on cultivating students' engineering practice ability, innovative thinking, teamwork, and professional ethos, enabling students to develop comprehensive competencies through solving real engineering problems [6].

2.2 Implementation Framework of CSITP under Industry-Education Integration

Based on the core connotation above, and combined with the implementation characteristics of engineering CSITPs and the development requirements of the grain depot fire safety early warning system, this paper constructs an implementation framework for industry-education integration CSITPs comprising “one core, two main lines, three stages, and four supports.” The framework specifies the goals, pathways, and supporting measures for project implementation, as illustrated in Fig. 1.

In Fig. 1, “one core” refers to cultivating students' engineering innovation capability as the central goal, around which all project activities are organized. The “two main lines” are the technical R&D line and the talent cultivation line: the former focuses on the development and on-site application of the grain depot fire safety early warning system, while the latter focuses on enhancing students' comprehensive competencies; the two lines integrate and reinforce each other. The “three stages” include the demand alignment and scheme design stage, the system development and debugging stage, and the field verification and achievement transformation stage; each stage builds progressively upon the previous one to ensure orderly progression and tangible results. The “four supports” encompass school-enterprise dual-mentor guidance, phased task-driven implementation, blended teaching resources, and school-enterprise jointly built practice bases, providing comprehensive safeguards for project implementation and ensuring that the principles of industry-education integration are put into practice [5].

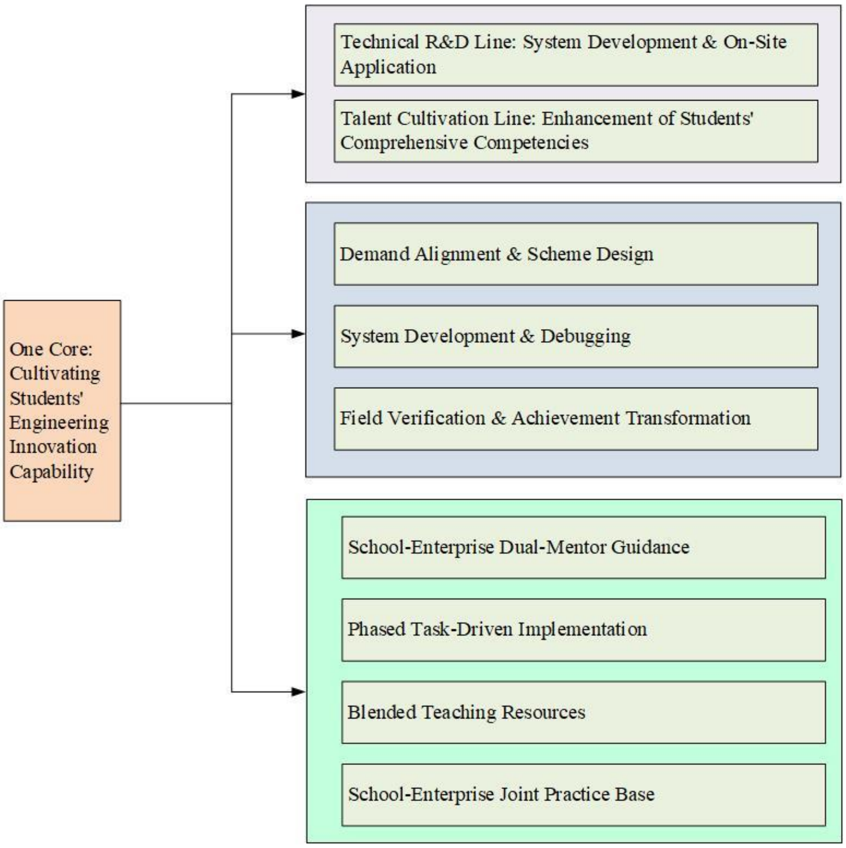

Fig. 1 Implementation Framework of CSITP under Industry-Education Integration

3. Project Background and Requirements Analysis

3.1 Industrial Background and Pain Point Analysis

As the world's largest grain producer and consumer, China maintained total grain reserves of over 600 million tons and operated more than 12,000 grain depots of various types by the end of 2025. As the core carrier for grain storage, the level of fire safety management in grain depots directly affects the security of national grain reserves [7]. However, fire safety management in China's grain depots remains at a relatively traditional stage, exhibiting the following prominent pain points that severely constrain the modernization of grain depot safety management:

1) Low manual inspection efficiency with significant blind spots: Traditional grain depot fire safety management relies primarily on manual instrument-based inspection, which involves high labor intensity and cannot achieve 24 hours uninterrupted monitoring. Moreover, the vast area and complex structure of grain depot warehouses leave many inspection blind spots, making it easy to miss potential fire hazards.

2) Delayed warning response: Conventional smoke and temperature sensors can only detect signals after a fire has already started, with warning response times of 3–5 minutes that often miss the optimal window for fire suppression and lead to rapid fire spread.

3) High false-alarm rates and insufficient reliability: Grain depot environments contain complex factors such as dust, steam, and lighting variations. Traditional sensors are easily affected by external interference, with false-alarm rates exceeding 15%, which increases management workload and may also lead managers to become desensitized to alarm signals.

4) Coarse-grained control: When fires occur, emergency operations such as ventilation, power cutoff, and fire extinguishing rely entirely on manual execution, resulting in slow response and risk of operational errors that could exacerbate losses.

5) Low informatization level: The lack of a unified remote monitoring platform prevents managers from grasping the safety status of various depot zones in real time. Monitoring data are difficult to share, analyze, and trace, hindering refined management [4,14].

With the rapid development of IoT, deep learning, and automatic control technologies, building intelligent and refined fire safety early warning systems for grain depots has become an inevitable industrial trend and an effective approach to addressing current pain points [8]. Against this background, the research team, supported by a national-level CSITP and in collaboration with the Xi'an National Grain Reserve Depot, undertook the development of a deep learning-based fire safety early warning IoT system for grain depots, achieving industry-education integration and school-enterprise collaborative talent cultivation.

3.2 Project Objectives and Positioning

Oriented toward solving practical fire safety problems in grain depots, leveraging industry-education integration as a key enabler, and centered on developing students' engineering practice and innovation capabilities, this project aims to develop a grain depot fire safety early warning system based on deep learning and IoT technology while exploring an implementation model for industry-education integration in engineering CSITPs. The specific objectives encompass technical and talent cultivation dimensions:

1) Technical objectives: Develop a grain depot fire safety early warning system integrating multi-source perception, intelligent recognition, PID precise control, and remote linkage; construct a dedicated grain-depot fire dataset; optimize the YOLOv8 deep learning model to achieve fire identification accuracy above 95% with false-alarm rate below 2%; achieve PID precise control of the ventilation system to automatically adjust airflow according to fire severity, reaching temperature control accuracy of ±0.5°C; develop accompanying upper-computer monitoring software and mobile APP supporting real-time remote monitoring and emergency operations; complete on-site testing and validation to produce a scalable technical solution.

2) Talent cultivation objectives: Through project implementation, students complete the full engineering workflow of “requirements analysis—scheme design—system development—testing & verification—on-site application,” gaining hands-on mastery of practical skills including IoT system construction, deep learning model training, PLC programming, and upper-computer software development; enhance students' engineering practice ability, innovative thinking, teamwork, and professional ethos; cultivate a cohort of interdisciplinary technical talents adapted to the demands of IoT and AI industries.

4. Project Design and Implementation under Industry-Education Integration

4.1 School-Enterprise Collaborative Project Team

To ensure the project's industrial relevance and engineering practicality, a collaborative innovation team consisting of "on-campus advisors + enterprise mentors + students" was formed, with clearly defined responsibilities and division of labor among members, achieving complementary strengths and collaborative talent cultivation between the university and enterprise.

During team operation, a routine communication mechanism was established with weekly project progress meetings. On-campus advisors focused on theoretical instruction and technical bottleneck guidance, while enterprise mentors emphasized engineering practice guidance and interpretation of industry standards. Students completed specific R&D tasks according to their division of labor, fostering a productive working atmosphere characterized by "school-enterprise collaboration, faculty-student interaction, and clear roles and responsibilities."

4.2 Phased Task-Driven Implementation Model

To ensure orderly project advancement and tangible outcomes, and aligned with both industry-education integration requirements and system R&D principles, this project adopted a task-driven teaching method, decomposing the entire project into 4 stages and 16 sub-tasks. Following the principle of "from simple to complex, progressing step by step," the tasks were advanced in phases, with clear definitions of dual-mentor responsibilities, student divisions, and evaluation criteria for each stage. This approach achieves synchronous advancement of project R&D and talent cultivation. Detailed task arrangements are shown in Table 1.

Table 1 Detailed Phased Task Arrangements of the Project

Stage	Task Arrangement
Demand Investigation and Scheme Design	1. On-site investigation of grain depot fire safety status; 2. Literature retrieval and analysis of related domestic and international technologies; 3. System requirements analysis and function definition; 4. Design and demonstration of overall technical scheme
Hardware Construction and Experimental Verification	1. Hardware selection and soldering of IoT sensing nodes; 2. Construction and debugging of IoT experimental box; 3. Construction and annotation of grain depot fire dataset; 4. Deep learning model training and preliminary optimization
System Integration and Platform Development	1. Integration and debugging of perception layer and control layer; 2. Development and optimization of PID control algorithm; 3. Development of upper-computer monitoring software; 4. Development of mobile APP
Field Testing and Outcome Summarization	1. On-site deployment and performance testing in grain depot; 2. System performance optimization and rectification; 3. Project paper writing and patent application; 4. Project acceptance and outcome demonstration

4.3 Blended Teaching Model Combining Virtual and Physical Practice

To improve project implementation effectiveness, and tailored to students' knowledge foundation and engineering practice needs, this project adopts a blended online-offline teaching model that integrates high-quality teaching resources from both inside and outside the university. This approach provides students with comprehensive learning support, organically integrating theoretical study with engineering practice. Specific implementation measures include:

1) Online resource self-study: Students were guided to study high-quality courses on the China University MOOC platform such as "IoT Technology," "Introduction to Artificial Intelligence," and "Fundamentals of PLC Programming"; video resources on Bilibili including YOLOv8 hands-on tutorials and Modbus protocol explanations; and official technical documentation for OMRON PLCs and frequency converters. These resources help students consolidate theoretical foundations and master core technical points.

2) Offline thematic teaching guidance: Regular thematic lectures, technical seminars, and group discussions were organized to address common issues encountered during project implementation (such as model optimization, hardware debugging, and communication fault diagnosis). Industry technical experts were invited to deliver specialized lectures introducing fire safety management standards and engineering practices for grain depots.
3) Virtual simulation experiments: An IoT experimental box was used to conduct virtual simulation experiments simulating fire scenarios and equipment failures, validating system functionality and control algorithms. This reduces field debugging risks and helps students familiarize themselves with system operation logic and debugging methods.
4) On-site practical training: Students were periodically organized to visit the Xi'an National Grain Reserve Depot for on-site learning and practice, gaining first-hand understanding of actual grain depot operations, safety management requirements, and equipment running environments. They participated in on-site data collection, equipment installation, and system debugging, accumulating engineering practice experience.

5. System Design and Implementation

5.1 Overall System Architecture

Combining the practical needs of grain depot fire safety management with the requirements of industry-education integration, this system adopts a four-layer architecture design comprising "perception layer—control layer—platform layer—application layer" [9]. The architecture balances the real-time nature of data acquisition, control precision, and remote management convenience, with standardized communication protocols enabling data exchange between layers. The overall architecture is shown in Fig. 2.

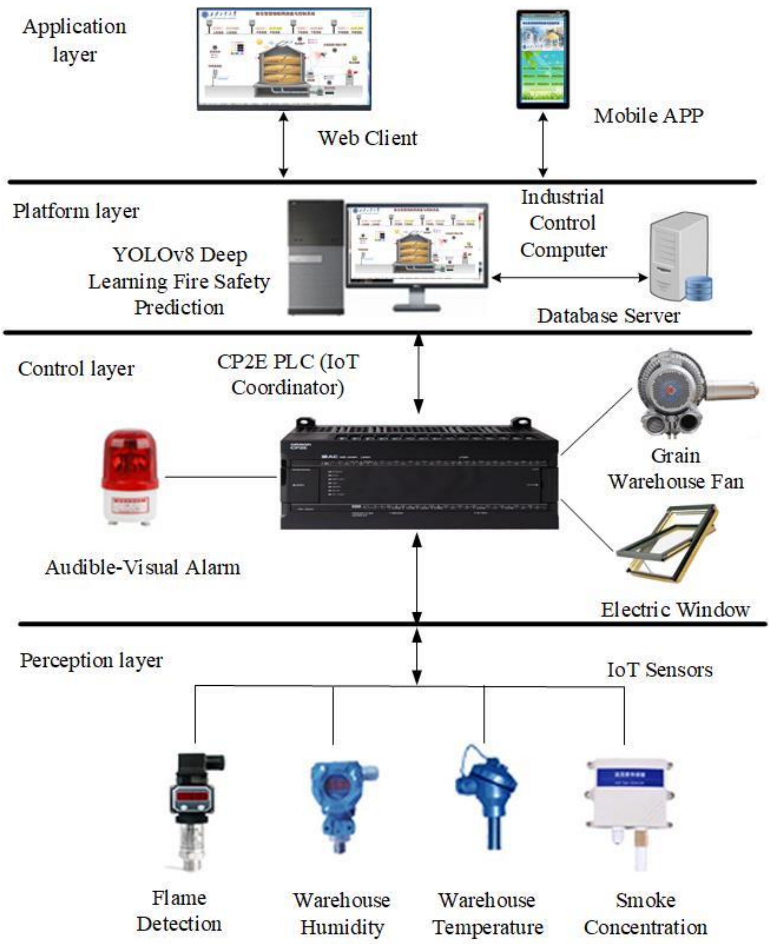

Fig. 2 Architectural Design of the Grain Depot Fire Safety Early Warning IoT System

The core functions of each layer are as follows:
1) Perception layer: Deployed inside grain depot warehouses and surrounding key areas, this layer serves as the data acquisition core of the system. It integrates temperature-humidity sensors, smoke sensors, ultraviolet flame sensors, and high-definition infrared cameras to comprehensively and continuously collect parameters such as temperature and humidity at each grain pile level, smoke concentration, and flame signals, providing reliable data support for subsequent intelligent recognition and control.
2) Control layer: Built around an OMRON CP2E series PLC as the core controller, this layer receives various data collected by the perception layer, executes PID control algorithms and emergency control logic, and drives actuators such as fans, electric windows, and audible-visual alarms to perform functions including ventilation cooling, fire warning, and emergency response.
3) Platform layer: Deployed on an industrial control computer, this layer serves as the system's core processing center, responsible for data storage, processing, and analysis. It runs the optimized YOLOv8 deep learning model for fire detection, enabling intelligent fire judgment, precise localization, and graded warning. The platform layer also handles communication management and parameter configuration.
4) Application layer: Provides a Web-based upper-computer monitoring software and a mobile APP, supporting remote real-time monitoring of grain depot safety status, viewing of historical data, receipt of alarm notifications, and remote control of on-site equipment, thus enabling refined and remote management of grain depot fire safety.

5.2 Hardware System Design

1) IoT Experimental Box Design: To meet the needs of system development, debugging, and educational training, and aligned with industry-education integration goals, this project designed and built an IoT experimental box that corresponds 1:1 with the field system. The experimental box integrates a grain warehouse controller and a multi-sensor array, with modular design that highly faithfully replicates real grain depot operating conditions. Its purpose is to translate abstract theory into intuitive engineering practice, comprehensively strengthening students' hands-on capability and system construction thinking. The box serves both as a tool for students to conduct experiments and master hardware debugging and system development skills, and as a platform for early-stage validation of system functions. The front view of the experimental box is shown in Fig. 3.
The experimental box adopts an industrial-grade modular design that allows easy disassembly, debugging, and maintenance by students. Its internal structure consists of the following core units:
(1) Core control unit: Uses an OMRON CP2E PLC controller responsible for data collection, logical operations, and control instruction output—the central control component of the experimental box.
(2) Perception unit: Integrates temperature-humidity sensors (DHT11), smoke sensors (MQ-2), and ultraviolet flame sensors (UV-Tron) to simulate the collection of grain depot environmental parameters and fire signals.
(3) Actuation uit: Includes a DC cooling fan (simulating the grain depot ventilation fan), LED indicators (simulating electric windows and alarm devices), and relay modules to receive control instructions and execute corresponding actions.
(4) Communication unit: Uses an industrial-grade wireless router supporting Wi-Fi and Ethernet communication, enabling wireless data exchange between the PLC, upper-computer, and mobile devices.
(5) Power unit: Uses a 24V DC switching power supply to provide stable power to all modules within the experimental box, ensuring stable system operation.

Fig. 3 Design of the IoT Experimental Box

2) On-Site Hardware Deployment: Based on investigation of the actual warehouse structure (mixed layout of single-story warehouses and silos) and fire-prevention requirements at a grain reserve depot in Shaanxi Province, this project adopts a grid-based deployment approach to ensure no monitoring blind spots and full control coverage. Specific deployment details are as follows:

(1) Perception equipment deployment: One temperature-humidity sensor and one smoke sensor are deployed every 200 m^2, installed at the upper, middle, and lower layers of the grain pile to collect real-time temperature, humidity, and smoke concentration data. One 2-megapixel infrared HD camera is deployed every 500 m^2, covering key areas such as the grain surface, work corridors, and electrical rooms for visual recognition of flames and smoke.

(2) Control equipment deployment: One OMRON CP2E PLC controller and one industrial control computer are deployed in each warehouse for local data processing and equipment control. Each warehouse is also equipped with one frequency converter to control fan operating frequencies for precise speed regulation.

(3) Alarm equipment deployment: Audible-visual alarms are deployed at warehouse entrances/exits and the control room. An emergency broadcasting system is deployed in the duty room to provide on-site warnings and emergency notifications.

(4) Communication equipment deployment: An industrial-grade switch and wireless router are deployed in the equipment room to construct a grain depot LAN, enabling high-speed communication between devices while supporting external network access for remote monitoring.

5.3 Software System Design

1) Upper-Computer Monitoring Software: A dedicated upper-computer software for the Smart IoT Grain Warehouse Measurement and Control System (V1.0) was developed in the Delphi language. The software adopts an MDI multi-document interface design and deeply integrates core functional modules including multi-source environmental monitoring, intelligent fire identification, and PID parameter tuning. It conforms to industrial control software operation standards and use habits, facilitating operation and maintenance by management personnel. The main interface is shown in Fig.4.

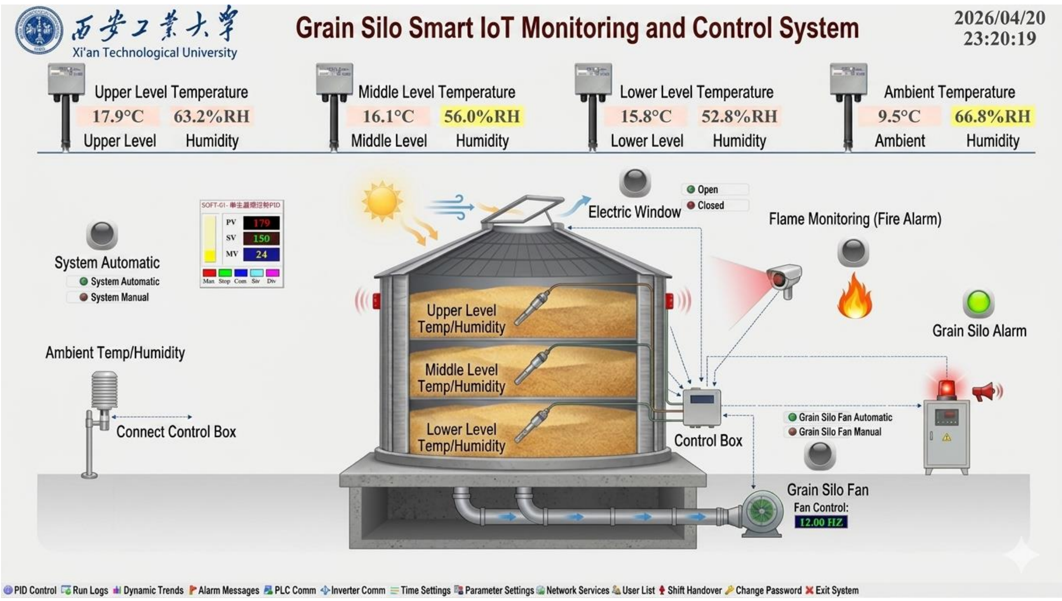

Fig. 4 Main Interface of the Smart IoT Grain Warehouse Measurement and Control System

The main functional modules are illustrated in Fig. 5.

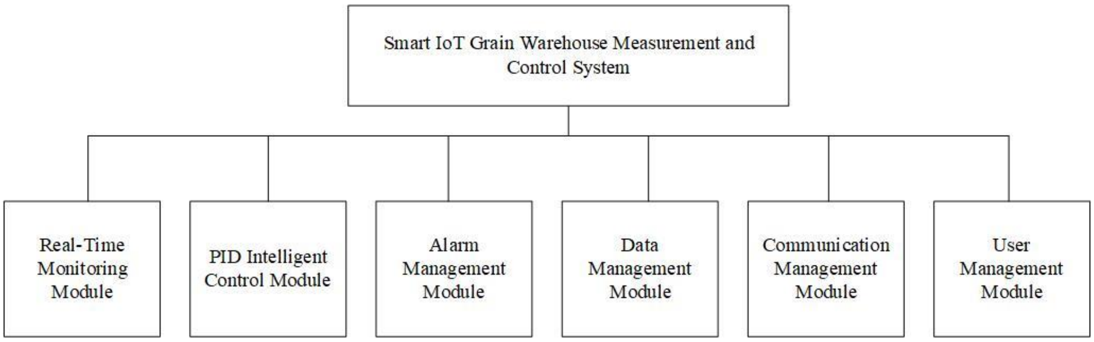

Fig. 5 Module Composition of the Smart IoT Grain Warehouse Measurement and Control System

The core functions of each module are as follows:

(1) Real-time monitoring module: Displays the grain warehouse structure and equipment distribution in 3D graphical form. Shows real-time parameters including temperature/humidity/smoke concentration/flame status at the upper, middle, and lower layers of the grain pile and the external environment. Also displays operating status of devices including electric windows, ventilation fans, and audible-visual alarms, as well as system alarm status.

(2) PID intelligent control module: Implements PID precise control of grain warehouse temperature, supports online adjustment of proportional coefficient (K_p), integral time (T_i), and derivative time (T_D) parameters, supports automatic/manual mode switching, and displays in real time the process value (PV), set value (SV), and manipulated variable (MV) of the PID controller.

(3) Alarm management module: Provides real-time alarms for abnormal conditions such as temperature/humidity exceedance, smoke exceedance, equipment failure, and fire. Records alarm time, type, location, and value in detail; supports alarm acknowledgment, reset, and historical alarm queries.

(4) Data management module: Automatically stores all historical monitoring data and equipment operation records. Supports precise queries by time range, equipment type, and parameter type. Data can be exported to Excel files. Dynamic trend curves are used to intuitively display parameter changes, providing support for grain condition analysis and fault diagnosis.

(5) Communication management module: Manages communication between the upper-computer and PLCs, frequency converters, sensors, and other devices. Supports Modbus TCP/RTU protocols.

Allows online viewing of communication status and debugging of communication parameters to ensure smooth and stable communication links.
(6) User management module: Supports multi-user permission management with three levels: administrator, operator, and inspector. Administrators have full permissions; operators can perform manual control and parameter viewing; inspectors can only view data and alarm information. This ensures system operational security and traceability.

Fig. 6 Main Interface of the Mobile APP for the Smart IoT Grain Warehouse Measurement and Control System

2) Mobile APP Design: A companion mobile APP was developed on the Android platform using the Java language and Android Studio development tool, achieving remote monitoring and management of grain warehouse safety. The APP is compatible with mainstream Android phone models. Its main interface is shown in Fig. 6.
The core functions of the APP include:
(1) Real-time monitoring: View in real time temperature/humidity/smoke concentration, equipment operating status, and alarm information for each warehouse. Supports switching between multiple warehouses for comprehensive monitoring.
(2) Remote control: Within permission limits, remotely control startup/shutdown and operating status of fans, electric windows, and other equipment for emergency response, improving management efficiency.
(3) Alarm push notifications: When abnormal conditions occur, the APP receives real-time alarm push notifications with clear display of alarm details and recommended responses. One-tap contact with relevant management personnel is supported, ensuring timely emergency response.
(4) Data query: Query historical monitoring data and alarm records, generate data reports, support export and sharing, providing data support for management decisions.
(5) User management: Supports multi-user login, password modification, and permission switching to safeguard secure and stable system operation.

5.4 Key Technology Implementation

1) YOLOv8-Based Fire Identification: To address the issues of high false-alarm rates and inability of traditional sensors to accurately identify fires, this project introduces deep learning technology, employing an optimized YOLOv8s model for intelligent identification of grain depot fires (flames and smoke), effectively improving the accuracy and real-time performance of fire identification [11,12].
(1) Dataset construction: Through a combination of on-site collection and web crawling, 12,000 flame and smoke images of real grain depot scenarios were collected to construct a dedicated GrainFire dataset, comprising 5,000 flame images, 4,000 smoke images, and 3,000 negative samples (normal grain depot scenarios). The dataset was annotated, deduplicated, and augmented through preprocessing to ensure diversity and accuracy, providing high-quality data support for model training [12].
(2) Model optimization: Two improvements were made on the basis of the YOLOv8s baseline model. First, the CBAM attention mechanism was introduced to enhance the model's feature extraction capability for flames and smoke, improving identification accuracy [13]. Second, Mosaic data augmentation was adopted, expanding the dataset through random cropping, flipping, and scaling to improve model generalization and prevent overfitting [14].
(3) Experimental results: To validate the optimized model's performance, comparative experiments were conducted under the same dataset and training environment (NVIDIA RTX 3060 GPU, input image resolution 640 × 640) against mainstream object detection models including Faster R-CNN, YOLOv5s, and YOLOv7-tiny. The experimental results are shown in Table 2.

Table 2 Performance Comparison of Different Fire Identification Models

Model	Precision	Recall	mAP@0.5	Inference Speed (FPS)	Model Size (MB)
Faster R-CNN	92.3%	89.7%	91.5%	8	167
YOLOv5s	93.8%	91.2%	92.7%	32	14
YOLOv7-tiny	94.5%	92.6%	93.4%	41	12
YOLOv8s (Baseline)	95.2%	93.7%	94.6%	43	11
YOLOv8s (Optimized)	96.5%	95.1%	95.8%	45	11

Note: Test environment is NVIDIA RTX 3060 GPU with input image size 640×640. The dataset is the GrainFire test set (1,200 images).

The simulation results show that the algorithm-optimized YOLOv8s model adopted in this system outperforms other comparison models in precision, recall, and mAP@0.5 metrics, while maintaining fast inference speed and small model size, with false-alarm rate below 2%—fully meeting the real-time and accuracy requirements for grain depot fire safety early warning.
2) PID Precise Ventilation Control: Precise control of grain depot temperature and humidity is critical to ensuring safe grain storage. This project employs a PID control algorithm to achieve variable-frequency speed regulation of grain warehouse fans. According to the deviation between the set grain temperature and real-time feedback, fan operating frequencies are automatically adjusted to achieve precise ventilation cooling and reduce energy consumption [15].
(1) Control algorithm principle: PID control is a classic automatic control algorithm that achieves precise control of the controlled object through the cooperative action of three components—proportional (P), integral (I), and derivative (D). Its core formula is given in Eq. 1:

$$u(t) = K_P\left[e(t) + \frac{1}{\tau i}\int_0^t (\tau)d\tau + T_d\frac{de(t)}{dt}\right] \tag{1}$$

where u(t) is the controller output, K_p is the proportional coefficient, T_i is the integral time, T_D is the derivative time, and e(t) is the deviation between the set grain temperature and real-time feedback.
(2) Parameter tuning: Initial parameter tuning was performed using the Ziegler-Nichols method. Combined with actual on-site conditions of the grain depot (standard single-story warehouse, grain

pile height 6 m, initial grain temperature 22°C, target grain temperature 18°C, ambient temperature 15°C), multiple comparative experiments were conducted to optimize PID parameters. The experimental results are shown in Table 3.

Table 3 Comparison of Control Effects with Different PID Parameter Combinations

Group	K_p	T_i (s)	T_D (s)	Max Overshoot (°C)	Settling Time (min)	Steady-State Error (°C)	Energy (kWh/day)
1	0.05	2000	0	2.3	45	±0.8	12.6
2	0.10	2000	0	1.7	32	±0.6	10.8
3	0.10	1500	0	1.2	25	±0.5	9.5
4	0.12	1200	50	0.7	18	±0.3	8.2

Note: Test conditions are a standard single-story warehouse with grain pile height 6 m, initial grain temperature 22°C, target grain temperature 18°C, and ambient temperature 15°C. Group 4 is the final optimized PID parameter combination.

(3) Optimization conclusion and control flow: Through multiple comparative experiments, parameter Group 4 ($K_p = 0.12$, $T_i = 1200$ s, $T_D = 50$ s) was identified as the optimal PID parameter combination. Under this parameter set, the system achieves a maximum overshoot of only 0.7°C, settling time reduced to 18 min, and steady-state error within ±0.3°C—significantly better than the project's technical target of ±0.5°C. Additionally, daily energy consumption is reduced to 8.2 kWh, representing a 35% reduction compared to Group 1, achieving the dual goals of precise temperature control and energy savings.

Based on the optimized PID parameters, a precise temperature-humidity control flow for the grain depot was designed: First, perception-layer temperature-humidity sensors collect real-time temperature/humidity data from each grain pile layer and transmit them via the communication unit to the control-layer PLC. Next, the PLC compares the real-time grain temperature with the set value (18°C), calculates the deviation e(t), and substitutes it into the PID algorithm to compute the output u(t). Then, the PLC adjusts the frequency converter frequency based on the output value, regulating fan operating speed and achieving precise ventilation control. Finally, the system feeds back the adjusted grain temperature data to form a closed-loop control, ensuring stable grain temperature within the set range. If the temperature deviation exceeds 2°C, the system automatically triggers an audible-visual alarm to prompt timely intervention by management personnel, further enhancing control reliability [16].

The application of this PID precise ventilation control technology effectively addresses the issues of coarse-grained ventilation control, high energy consumption, and insufficient temperature control accuracy in traditional grain depots, providing reliable technical support for safe grain storage. It also enables students to gain hands-on mastery of PID algorithm principles, parameter tuning methods, and engineering applications, fulfilling the educational goals of industry-education integration.

6. Project Implementation Outcomes and Reflections

6.1 Project Implementation Outcomes

This project advanced strictly according to the industry-education integration framework, achieving bidirectional empowerment between technical R&D and talent cultivation. Significant industrial application and educational outcomes were achieved, manifested in the following two aspects:

1) Industrial Application Outcomes: The deep learning-based grain depot fire safety early warning IoT system developed by the project has completed preliminary on-site deployment and testing at an enterprise in Shaanxi Province. The system runs stably with excellent performance, fully meeting the practical needs of grain depot fire safety management. Through on-site testing combined with simulation validation, the system achieves fire identification accuracy of 96.5%, false-alarm rate of

only 1.8%, and warning response time reduced to within 30 seconds—an improvement of over 90% compared to traditional management modes. PID precise temperature control accuracy reaches ±0.3°C, with grain depot ventilation energy consumption reduced by 35%, effectively mitigating safety risks such as grain mildew and fire.

2) Talent Cultivation Outcomes: Through project implementation, students completed the full engineering R&D workflow, with significant improvements in their comprehensive capabilities. In terms of technical capability, team members gained hands-on mastery of practical skills including IoT system construction, deep learning model training, PLC programming, and upper-computer and mobile APP development. Three students received second prizes in university-level computer design competitions, and one student secured an internship offer from a domestic enterprise based on the project outcomes. In terms of innovation and collaboration, students cultivated innovative thinking and problem-solving skills while addressing real-world issues such as system integration, model optimization, and field debugging. Their teamwork awareness and communication skills were also effectively strengthened. In terms of professional ethos, through enterprise on-site practice and industry-standards study, students gained deep understanding of professional norms and engineering requirements in engineering disciplines, internalizing the engineering philosophy of “demand orientation and pursuit of excellence” and laying a solid foundation for future career development.

6.2 Project Implementation Reflections

While significant outcomes were achieved during project implementation, several issues and shortcomings were also identified, providing experiential references for similar future projects:

First, the depth of school-enterprise collaboration still needs to be strengthened. Currently, enterprise mentors are mainly involved in technical guidance and field validation, with insufficient participation in initial topic selection requirements investigation and scheme design phases. This led to minor deviations between some technical schemes and actual industrial needs. Future improvements should refine the school-enterprise dual-mentor mechanism to engage enterprises throughout the entire project lifecycle.

Second, students' engineering practice capabilities vary. Some students lack first-line engineering practice experience, resulting in low efficiency in hardware debugging and on-site deployment phases. Future iterations should optimize the blended teaching model and increase on-site practice hours to enhance students' engineering execution capabilities.

Third, outcome transformation efforts remain insufficient. Currently, project outcomes mainly remain at the simulation testing and pilot application stage. Some key technologies within the system are still being optimized and cannot yet support large-scale industrialization. Future work needs to deepen cooperation with enterprises, refine the outcome transformation mechanism, drive the practical application of technical results, and truly achieve the integration of industry, academia, research, and application in industry-education integration.

7. Conclusion and Prospects

7.1 Conclusion

This paper takes the national-level CSITP “Grain Depot Fire Safety Early Warning IoT System Based on Deep Learning” as the carrier to explore implementation pathways and models for engineering CSITPs under industry-education integration. The following conclusions are drawn:

1) CSITPs under industry-education integration must center on real industrial needs and construct a full-chain practice system of “industrial demand—scheme design—system development—on-site verification—achievement transformation” to effectively address the “industry-education disconnect” issue and achieve bidirectional empowerment between technical R&D and talent cultivation.

2) The implementation model combining school-enterprise dual-mentor guidance, phased task-driven implementation, and blended teaching with virtual-physical practice can effectively improve project implementation quality. It ensures both the industrial practicality of project outcomes and

significantly enhances students' engineering practice ability, innovative thinking, and team collaboration competencies.

3) The developed grain depot fire safety early warning IoT system effectively addresses the prominent pain points of traditional fire safety management, demonstrating strong industrial application value and promotional potential. It also provides a replicable and scalable practical case for industry-education integration in similar engineering CSITPs.

7.2 Prospects

Looking ahead, future work will address the issues identified during project implementation by further deepening industry-education integration, refining the school-enterprise collaborative talent cultivation mechanism, and engaging enterprises throughout the full project lifecycle—from topic selection and scheme design to R&D implementation and outcome transformation. On the technical front, the deep learning model will be further optimized and edge computing will be introduced to reduce deployment costs and improve real-time performance and reliability. Additional functional modules such as grain pest detection and grain quality monitoring will be added to construct a comprehensive smart grain depot management system. On the talent cultivation front, the project implementation model will be further optimized and expanded to engage more students in industry-education integration innovation practices. This will cultivate more interdisciplinary engineering innovation talents adapted to industrial upgrading needs, support the in-depth advancement of higher engineering education reform, and provide talent and technical safeguards for national grain security and high-quality industrial development.

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References

[1] State Council of the People's Republic of China: Several Opinions on Deepening Industry-Education Integration. (2017).

[2] Ministry of Housing and Urban-Rural Development of the People's Republic of China: GB 50016-2014 Code for Fire Protection Design of Buildings (2018 Edition). (China Planning Press, Beijing 2018).

[3] F. Cui and J. Cao: Journal of Yancheng Teachers University (Humanities and Social Sciences Edition), Vol. 45 (2025) No.2, p.73.

[4] C.H. Lin, Z.R. Zhang, J.T. Zhuo, et al.: Innovation and Entrepreneurship Theory Research and Practice, Vol. 7 (2024) No.11, p.61.

[5] X.H. Ma: Industrial Innovation Research, (2023) No.14, p.196.

[6] T.T. Ma: China Market, (2022) No.6, p.56.

[7] Y. Liu and H.J. Yan: Internet of Things Technologies, Vol. 15 (2025) No.20, p.133.

[8] M. Kou: China Food Safety Magazine, (2025) No.13, p.176.

[9] Y.X. Sheng: Research on Intelligent Collaboration of Food Security Based on Multi-Source Data Fusion (M.S., Jilin University, China 2025).

[10] State Administration of Grain and Material Reserves: Compilation of Scientific and Technological Achievements in Grain and Material Reserves (State Administration of Grain and Material Reserves, Beijing 2024).

[11] X.J. Fang, X.F. Jiang, L.Q. Xu, et al.: Journal of Electronics & Information Technology, Vol. 47 (2025) No.6, p.1976.

[12] J. Sun and S.S. Zhang: Journal of Xinyang Normal University (Natural Science Edition), Vol. 38 (2025) No.2, p.152.

[13] Y.D. Su, Y.K. Xie, Y.J. Zhao, et al.: Modern Tunnelling Technology, Vol. 62 (2025) No.6, p.92.

[14] M. Li, Y.S. He, J.B. Lu, et al.: Computer Systems & Applications, Vol. 31 (2022) No.11, p.230.

[15] X.Y. Sun, W.W. Wang and Z.M. Li: Cereal & Feed Industry, (2026) No.1, p.74.
[16] X.J. Shi, Z.Q. Xiang, Y.G. Chen, et al.: Coal Mine Safety, Vol. 57 (2026) No.3, p.176.