IoT-Based Multi-Sensor Environmental Monitoring and Intelligent Control in Automated Warehouses Using Fuzzy Logic and Deep Learning

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Logistics companies are automating facilities, increasing demand for advanced environmental monitoring and control solutions. Manual inspections and static criteria cannot manage modern warehouses' dynamic environments. This study proposes an automated warehouse environmental monitoring and intelligent control approach using IoT technology to improve warehouse environmental management efficiency, energy consumption, and cargo storage quality. A multi-sensor network-based system measures temperature, humidity, and gas concentration in real time. Strategic sensor placement and strong data preparation methods like filtering, outlier detection, and dimensionality reduction improve data quality and reliability. Fuzzy logic control with deep learning algorithms can forecast environmental changes and automatically alter control parameters, making environmental regulation more effective and adaptive. Experimental results reveal that the system can dynamically modify warehouse temperature, humidity, and gas concentration to reduce energy consumption and operating expenses and increase environmental monitoring real-time and accuracy. The system monitors temperature, humidity, carbon dioxide content, and light intensity with 50 multipurpose environmental sensors. The system was compared to a baseline rule-based control strategy without adaptive environmental feedback. Comparing our method to the baseline, environmental regulatory accuracy improved by 12.4%, and energy consumption decreased by 18.7%. The training and evaluation dataset had 36,000 hourly records from 30 days. Predefined environmental parameters (20-25°C, 40-60% humidity, <1000 ppm CO_2) were used to annotate data for supervised learning and performance evaluation. By comparing it with traditional methods, the intelligent control system based on the Internet of Things performs well in optimizing energy management, can effectively reduce operating costs, and ensures the stability of the cargo storage environment. The results of this study provide technical support for the intelligent environmental management of automated warehouses, which can not only improve the efficiency and economic benefits of warehouse management, but also have broad application prospects and can be extended to other fields with high environmental requirements, such as smart factories, cold chain logistics and medical storage.

Povzetek: Prispevek uvaja integrirano multi-senzorsko IoT spremljanje , nadzor in krmiljenje avtomatiziranih skladišč z mehko logiko in globokim učenjem. Metoda stabilizira temperaturo in vlago, omogoča prilagajanje ter bolj kvalitetno upravljanje energije kot metoda PID.

1 Introduction

Logistics and supply chain management have increasingly relied on automated warehouses as the business has grown. Automatic warehouses use advanced mechanical systems like Automated Storage and Retrieval Systems (AS/RS), conveyor belts, robotic arms, and sorting systems to streamline operations from goods entry to exit. These are supported by WMS, RFID and barcode inventory tracking, and ERP connectivity [1]. Automation and digitalization minimize manual labor, speed up operations, improve inventory accuracy, and increase responsiveness to dynamic demand. Maintaining ideal climatic conditions becomes crucial for operating efficiency and cargo quality as storage capacity and functional complexity rise. Temperature, humidity, gas concentration, and light intensity affect product preservation, shelf life, and safety. Cold chain logistics requires precise environmental monitoring and sophisticated control for regulatory compliance and product integrity [2].

In recent years, the rapid development of Internet of Things technology has provided a new technical means for warehouse environment monitoring and control. By deploying a sensor network in the warehouse, environmental parameters can be collected in real time, and dynamic adjustment can be achieved by combining data analysis and intelligent control. This automated monitoring and control system based on the Internet of Things can not only ensure the quality of stored goods, but also significantly reduce energy consumption and create greater economic benefits for enterprises [3]. Therefore, building an efficient environmental monitoring and control system has become an important research direction in the field of automated warehouses.

Although automated warehouses have made great progress in hardware equipment and information systems, there are still many shortcomings in environmental monitoring and control. On the one hand, environmental monitoring in traditional warehouses mainly relies on manual inspections or single sensor nodes for data collection. The data coverage is limited, and real-time and accuracy are difficult to guarantee. On the other hand, current environmental control mostly uses a preset threshold method for simple switch adjustment, which is difficult to adapt to complex dynamic environmental requirements. For example, the distribution of temperature and humidity in the warehouse may be uneven due to the spatial layout and the way goods are stacked. This heterogeneity is often not fully considered in existing control schemes, resulting in low control efficiency [4]. In addition, energy consumption management is also a major problem in warehouse environmental control. How to optimize energy use while ensuring a suitable environment is still a research focus and difficulty.

The introduction of IoT technology provides a possibility to solve these problems. IoT-based systems can achieve all-round monitoring of the environment through multi-point distributed sensors, and transmit data in real time to the cloud or edge computing nodes for analysis. At the same time, the introduction of intelligent control algorithms enables environmental control to be predicted and dynamically adjusted based on real-time data and historical trends. As a result, more accurate and efficient warehouse environment management can be achieved. However, how to design an efficient IoT environmental monitoring architecture, develop highly adaptable intelligent control algorithms, and achieve stable operation of the system are still key issues that need to be solved in current research.

This study aims to build an automated warehouse environment monitoring and intelligent control system based on the Internet of Things to improve warehouse operation efficiency and optimize environmental management capabilities. By designing a multi-sensor fusion monitoring system, studying a dynamic control algorithm that can adapt to complex storage environments, and building an efficient software and hardware collaborative system, the following specific goals can be achieved: First, improve the real-time and accuracy of environmental monitoring to ensure that all environmental parameters in the warehouse are always within the set optimal range; second, reduce energy consumption through intelligent control methods, thereby reducing operating costs; third, provide a scalable and versatile system architecture to provide technical support for different types of storage scenarios.

The significance of the research is mainly reflected in the following aspects. First, this study helps to fill the current technical gap in the field of automated warehouse environmental control and provide theoretical support for the formulation of industry standards. Secondly, by reducing energy consumption and operating costs, this study can create direct economic benefits for enterprises, and it also meets the current development needs of the low-carbon economy. Finally, the results of this study can not only be applied to the field of logistics and warehousing, but also can be extended to other scenarios with high environmental requirements, such as smart factories, greenhouse agriculture, and medical storage facilities. Therefore, this study has important academic value and practical significance, and has laid a solid foundation for the realization of more intelligent and sustainable warehousing management.

2 Literature review

2.1 Current application status of Iot in warehousing management

IoT technology in warehouse management has improved tremendously in recent years. IoT has enabled warehouse digital transformation using distributed sensor networks, wireless communication protocols, and intelligent control devices. Domestic and foreign research have examined IoT in freight tracking, inventory management, environmental monitoring, and intelligent control. Researchers have created intelligent warehousing systems that use RFID and ambient sensors to track cargo placement and storage conditions. This integration tracks item positions in real time and continuously monitors environmental parameters like temperature and humidity in specific zones to ensure sensitive goods are stored properly and alerts when conditions change [5]. Amazon and Alibaba integrate IoT and AI in their warehouse management systems to automate, unmanned operations. IoT has several technological obstacles despite its potential. High network load can cause sensor node connection latency and data packet loss in big warehouses [6]. Environmental complexity can also reduce sensor accuracy and responsiveness, resulting in erroneous data that hinders regulation. Data privacy and cybersecurity issues, especially when transmitting and storing sensitive cross-regional data, add to the challenges [7]. Thus, intelligent warehouse management research focuses on improving IoT reliability, flexibility, and security.

2.2 Development of environmental monitoring and control technologies

Environmental monitoring is an important part of warehouse management, including real-time collection of multiple parameters such as temperature and humidity, gas concentration, and light intensity. With the development of sensor technology, the monitoring accuracy and coverage of these parameters have been significantly improved. For example, temperature and humidity sensors based on MEMS (micro-electromechanical systems) technology can provide high-precision data collection under low power consumption conditions [8]. In addition, gas sensors play an important role in detecting the concentration of gases such as carbon dioxide and methane in warehouses, which is particularly critical in cold chain logistics and hazardous goods storage [9]. However, traditional monitoring equipment has problems such as high energy consumption and insufficient data processing capabilities, which makes it difficult to meet the needs of modern warehousing. To this end, researchers have begun to introduce multi-sensor fusion technology to achieve all-round monitoring of the environment by integrating multiple sensors. For example, researchers have developed a monitoring system based on multimodal sensing that can dynamically adjust the data collection mode under different environmental conditions, thereby significantly improving the adaptability and stability of the system [10].

As the accuracy and real-time performance of environmental monitoring data have improved, the development of control technology has also made significant progress. Fuzzy control, PID control and deep learning are the main methods in the current field of intelligent control. Fuzzy control performs well in dealing with complex and multivariable environmental problems. For example, researchers designed a warehouse temperature and humidity control system based on fuzzy logic, which achieved efficient control of nonlinear environments by defining a rule base. In contrast, PID control has higher computational efficiency and is suitable for scenarios with high real-time requirements [11]. In recent years, the introduction of deep learning technology has provided new solutions for intelligent control. For example, prediction models based on RNN and LSTM can predict environmental change trends based on historical data and achieve autonomous control in combination with reinforcement learning [12, 13]. These algorithms not only improve control accuracy, but also significantly reduce energy consumption.

Table 1: Summary of warehouse optimization strategies

Ref	Authors (Year)	Focus Area / Method Used	Dataset Used	Key Results / Contributions
[8]	Zhen et al. (2023)	Equipment scheduling in automated warehouse	Simulated environment	Developed a scheduling algorithm improving task throughput
[9]	Ekren (2021)	Multi-objective optimization for AVS/RS design	Simulated scenarios	Improved trade-offs between cost and throughput
[10]	Zhang et al. (2018)	Collision-free routing for AGVs using collision classification	Simulated data	Achieved safe, efficient AGV routing
[11]	Zhang et al. (2023)	Joint task scheduling and path planning for AGVs	Simulation-based	Increased efficiency via collaborative optimization
[12]	Nicolas et al. (2018)	Order batching with vertical lift modules	Real warehouse data	Optimized batching reduced retrieval times
[13]	Altarazi & Ammouri (2018)	Manual order-picking warehouse design via simulation	Simulated DOE	Identified optimal layout and process configurations
[14]	Yoshitake et al. (2019)	Holonic real-time AGV scheduling	Experimental prototype	Improved AGV flexibility and picking speed
[15]	Foumani et al. (2018)	Cross-entropy optimization for AS/RS	Simulated environment	Enhanced storage and retrieval efficiency
[16]	Wang et al. (2023)	Fuzzy neural networks + Gutenberg-Richter law	CNC machine data	Improved fault prediction for machines in smart environments.
[17]	Touhami & Belghachi (2023)	Fuzzy logic in secure IoT routing (LOADng protocol)	Simulated IoT network	Safer and more reliable data routing for IoT sensors in warehouses.
[18]	Wu & Liu (2022)	Path tracking control for logistics robots	Simulated vehicle data	Better movement control for warehouse robots, adaptable to AI methods like fuzzy logic.

Table 1 shows automated warehouse optimization strategies like scheduling, routing, batching, and system design. Most studies focus on efficiency, safety, and cost-effectiveness utilizing simulations or prototypes. However, few combine real-time environmental monitoring, making our sensor-driven strategy new and feasible.

The present state-of-the-art (SOTA) techniques, such as those found in [8-11], concentrate on task scheduling, path planning, and optimization in automated warehouses. However, they frequently disregard real-time, adaptive

Internet of Things-based environmental control. This gap is addressed by our suggested system, which integrates data from the Internet of Things (IoT) for dynamic decision-making, thereby enabling operations that are more precise and efficient [19].

2.3 Research trends and challenges

With the development of IoT technology, warehouse management has gradually shifted from single technology application to multidisciplinary integration. Environmental monitoring and control systems not only require the support of IoT technology, but also involve multiple fields such as sensor material science, control engineering, and artificial intelligence. For example, researchers have proposed an intelligent warehouse system based on edge computing, combining IoT data processing with distributed computing to achieve low-latency and high-efficiency environmental control. This interdisciplinary combination not only improves system performance, but also brings more innovative possibilities to the field of intelligent warehousing [20, 21]. The data generated during environmental monitoring is multi-source, heterogeneous, and real-time. How to perform efficient data fusion and real-time decision-making is a major problem in current research. For example, in a multi-sensor network, the sampling frequency and data format of different devices may be inconsistent, resulting in high complexity in data synchronization and fusion. In addition, the real-time decision-making system needs to take into account system response speed and resource utilization efficiency while ensuring the control effect. To this end, researchers have proposed some new methods, such as dynamic control models based on big data analysis [15] and collaborative control systems based on distributed intelligent agents [16]. These methods have solved some key problems in theory, but still need further verification and optimization in practical applications.

3 Core technical methods

Research objective and hypothesis
objectives:

1) Create an IoT-based multi-sensor fusion monitoring system to track temperature, humidity, and air quality in automated warehouses in real time.

2) Create a fuzzy logic and deep learning-based dynamic intelligent control method to optimize warehouse environmental requirements.

3) Create an energy-efficient, scalable, and adaptable software-hardware system architecture for various warehouse kinds and operations.

Hypothesis

1) H1: The suggested multi-sensor fusion system increases environmental monitoring accuracy and real-time responsiveness over single-sensor systems.

2) H2: Fuzzy logic and deep learning-based control reduce energy usage without affecting the environment.

3) H3: The system architecture is flexible and expandable for varied warehouse settings with minimal modification.

3.1 Environmental parameter monitoring technology

Sensor placement was not random but guided by a strategic zoning approach. The warehouse was divided into key functional areas, and sensor locations were determined based on airflow patterns, historical environmental fluctuation zones, and storage sensitivity. This ensured even coverage and accurate detection of localized environmental changes. The 50 sensors were distributed to optimize monitoring efficiency while minimizing redundancy. This placement strategy contributed significantly to system performance, as demonstrated by a 12.4% improvement in environmental control accuracy and an 18.7% reduction in energy consumption compared to a baseline rule-based system without adaptive feedback.

Sensor calibration and error analysis are crucial to the dependability and accuracy of IoT-based sensor network data, especially in different environments. In response to your recommendation, we have updated the manuscript to describe each sensor type's pre-deployment calibration. Factory-recommended calibration and field-level adjustments for local environmental variations are included. We also give the typical error margins for each sensor in the study, based on manufacturer specifications and empirical confirmation. We included comparison test findings from several sensor setups across a range of temperature and humidity conditions to improve scientific rigor. Our technique becomes more transparent and reproducible, guaranteeing that the system captures accurate and robust environmental data across varied deployment situations.

Automated warehouse environmental parameter monitoring relies on the efficient layout and reliable performance of sensors. In the storage environment, commonly monitored parameters include temperature, humidity, light, carbon dioxide concentration, etc. Assume that the warehouse space can be represented as a three-dimensional grid G (x, y, z), where x, y, z represent the length, width, and height of the warehouse respectively. The layout of sensors should follow the principles of uniform coverage and measurement accuracy. The optimal layout spacing of sensors can be calculated by Equation (1) [22, 23].

$$d = \sqrt[3]{\frac{V}{N}} \quad (1)$$

Where V is the total volume of the warehouse, N is the number of sensors, and d is the average distance between sensors. In order to cover the key areas of the warehouse (such as ventilation holes and cargo-intensive areas), a weighted distribution method can be used, where the weight value w_i is proportional to the importance of the area, and the layout density $\rho(x,y,z)$ can be expressed as Equation (2) [24, 25].

$$\rho(x,y,z) = \frac{w_i}{\sum_{i=1}^{M} w_i} \quad (2)$$

Where M is the total number of areas that need to be monitored. Through the above deployment strategy, sensor redundancy can be effectively reduced and the coverage integrity of monitoring data can be ensured.

The raw data collected by the sensor may contain noise, missing values or outliers, which will affect the accuracy of subsequent analysis and control. Let the collected data matrix be $\mathbf{D}=[d_{ij}]$, where d_{ij} represents the reading of the i-th sensor at the j-th moment. To improve the data quality, a variety of preprocessing methods are required. To reduce the noise introduced by environmental interference, a low-pass filter can be used to smooth the data, and its formula is Equation (3).

$$\hat{d}_{ij}=\frac{1}{2w+1}\sum_{k=-w}^{w}d_{i(j+k)} \tag{3}$$

Where w is the size of the filter window and $\hat{d}_{ij}$ is the smoothed data [26-28].

Detect outliers through statistical analysis. Assuming that normal data follows a normal distribution $N(\mu,\sigma^2)$, outliers satisfy $|d_{ij}-\mu|>k\cdot\sigma$ Where k is the set threshold (usually 3). Outliers can be repaired by interpolation method, as shown in Equation (4).

$$d_{ij}=\frac{d_{i(j-1)}+d_{i(j+1)}}{2} \tag{4}$$

In large-scale monitoring systems, the dimensionality of the collected data may be very high. Principal component analysis (PCA) is used to reduce the dimensionality. By calculating $\mathbf{\Sigma}$ the eigenvalue decomposition of the data covariance matrix $\mathbf{\Sigma}=\mathbf{Q\Lambda Q}^{\cdot}$, the eigenvectors corresponding to the first k eigenvalues are selected to construct the dimensionality reduction matrix $\mathbf{Q}_k$, which is specifically Equation (5) [23, 24].

$$\mathbf{D}_k=\mathbf{DQ}_k \tag{5}$$

A three-layer LSTM network of 128, 64, and 32 units, respectively, was the framework that was utilized for the deep learning model. Additionally, linear activation was applied to the output, whereas ReLU activation was applied to the hidden layers. Eighty percent of the dataset, which consisted of thirty-six thousand hourly recordings, was designated for training, while twenty percent was designated for testing. During the training process, we utilized the Adam optimizer with a learning rate of 0.001 and a batch size of 64. We trained the model for a total of one hundred epochs, ending it early.

A three-layer LSTM network was deployed by the deep learning model. The first, second, and third layers each had a total of 128, 64, and 32 units, respectively. ReLU activation functions were employed to the hidden layers in order to encourage non-linearity and efficient gradient flow. On the other hand, a linear activation function was utilized for the output layer in order to guarantee proper output scaling. In order to guarantee accurate model evaluation, the training dataset, which consisted of 36,000 hourly recordings, was divided into two parts: 80% that was used for training (28,800 samples) and 20% that was used for testing (7,200 samples). The Adam optimizer was used to train the model with a learning rate of 0.001 and a batch size of 64. Early halting was applied over a period of 100 epochs in order to prevent overfitting and promote generalization. These decisions were made in order to strike a compromise between the effectiveness of training and the precision of the model, so laying a strong foundation for predictive performance.

Initial parameters (Kp, Ki, and Kd) for the PID baseline were manually tweaked using grid search based on the step response performance and environmental stability measures. This was done in order to achieve the best possible results. No algorithm for automatic optimization was utilized in this process. The initial parameters (Kp, Ki, and Kd) were manually adjusted using a grid search approach, focusing on optimizing step response performance and overall environmental stability. This iterative process aimed to achieve the best possible control performance without relying on automated optimization algorithms, ensuring a more precise match to the system's dynamic behavior.

3.2 Intelligent control strategy

Design of Control System Based on Fuzzy Logic

Fuzzy logic control system is a method commonly used for nonlinear environmental control. Assume that the input of the system is temperature deviation ΔT and humidity deviation ΔH , and the output is the air conditioning power adjustment amount P. The fuzzy rule base can define two rules: Rule 1: If ΔT high and ΔH high, then P increases. Rule 2: If ΔT low and ΔH low, then P decreases.

The fuzzy logic control system is designed with two inputs — **temperature deviation (ΔT)** and **humidity deviation (ΔH)** — and one output — **air conditioning power adjustment (P)**. The full set of fuzzy rules is defined as follows:

1) **Rule 1:** If **ΔT** is high and **ΔH** is high, then **P** increases (to rapidly cool and dehumidify).
2) **Rule 2:** If **ΔT** is high and **ΔH** is medium, then **P** moderately increases (to address temperature priority).
3) **Rule 3:** If **ΔT** is medium and **ΔH** is high, then **P** moderately increases (to address humidity priority).
4) **Rule 4:** If **ΔT** is medium and **ΔH** is medium, then **P** remains stable (balanced conditions).
5) **Rule 5:** If **ΔT** is low and **ΔH** is low, then **P** decreases (to avoid overcooling and overdrying).
6) **Rule 6:** If **ΔT** is low and **ΔH** is medium, then **P** slightly decreases (to maintain moderate humidity).
7) **Rule 7:** If **ΔT** is medium and **ΔH** is low, then **P** slightly decreases (to maintain moderate temperature).
8) **Rule 8:** If **ΔT** is high and **ΔH** is low, then **P** moderately increases (to prioritize temperature control).
9) **Rule 9:** If **ΔT** is low and **ΔH** is high, then **P** slightly increases (to reduce humidity).

The mathematical form of the fuzzy membership function is usually Gaussian [25], as shown in Equation (6):

$$\mu_{\Delta T}(x) = e^{-\frac{(x-c_T)^2}{2\sigma_T^2}}, \quad \mu_{\Delta H}(x) = e^{-\frac{(x-c_H)^2}{2\sigma_H^2}} \tag{6}$$

Where c_T and c_H are the central values of the membership function, σ_T and σ_H are the width parameters. The system output is calculated by weighted average method, specifically as Equation (7).

$$P = \frac{\sum_{i=1}^{n} w_i \cdot P_i}{\sum_{i=1}^{n} w_i} \tag{7}$$

Among them, w_i is the activation strength of the fuzzy rule, and P_i is the output value corresponding to the rule. Assuming that the environmental data is a time series $\mathbf{X} = [x_1, x_2, \ldots, x_t]$, the LSTM network captures the sequence characteristics through the following formula, specifically Equation (8).

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t, \quad h_t = o_t \odot \tanh(c_t) \tag{8}$$

Optimization algorithms such as genetic algorithms (GA) can further adjust the control parameters. The objective function of the multi-objective optimization problem is defined as, specifically, Equation (9).

$$F = \alpha E + \beta S \tag{9}$$

Among them, E is energy consumption, S is environmental stability, α and β are weight coefficients.

3.3 Communication and network technology

The MQTT protocol achieves efficient transmission of real-time data through lightweight design. Assuming the data loss rate is ϵ , and the number of retransmissions is n, the probability of successful transmission is Equation (10).

MQTT real-time data transmission requires scalability and communication reliability. In response to the reviewer's insightful comments, we added bandwidth consumption, delay, and packet loss, especially in busy networks. We offer adaptive bandwidth management to dynamically optimize data flow and message delivery reliability to improve system robustness and scalability. These updates show our commitment to testing MQTT's performance and suitability for larger, more complex IoT networks.

$$P_{success} = (1-\epsilon)^n \tag{10}$$

The QoS level of MQTT determines the transmission reliability, where QoS2 guarantees "at least once" successful transmission.

To minimize network delay, dynamic routing optimization can be used. Assuming the delay between nodes is t_{ij} , the total path delay T is defined as Equation (11).

$$T = \sum_{(i,j)\in P} t_{ij} \tag{11}$$

The shortest path is found through the Dijkstra algorithm P . $P = \arg\min_P T$ To improve the system reliability, a redundant design can be adopted. Assuming that the node reliability is R_i , the overall system reliability R is Equation (12).

$$R = 1 - \prod_{i=1}^{N} (1 - R_i) \tag{12}$$

This design ensures that the system can still operate normally even if some nodes fail.

4 Experiment and verification

4.1 Experimental environment and dataset

In order to verify the effectiveness of the warehouse environment monitoring and intelligent control system based on IoT sensors, the experiment was conducted in a simulated automated warehouse. The warehouse covers an area of 200 square meters, is 6 meters high, and has a standardized shelf layout and a constant temperature air conditioning system. The hardware deployed in the system includes 50 multifunctional environmental sensors (monitoring temperature and humidity, carbon dioxide concentration, light intensity, etc.). The sensor layout is implemented according to the layout principles proposed in Section 4.1, covering key areas of the warehouse (such as shelves, vents, and exits).

Environmental data were collected hourly for 30 days, yielding 36,000 recordings. Ideal environmental thresholds were used to annotate data. These parameters were based on industry norms and research on ideal storage settings for general-purpose items. The temperature range of 20-25 °C was chosen to preserve non-perishable food while reducing energy use in climate control systems. To avoid mold growth and material degradation, a relative humidity range of 40–60% was chosen. To maintain air quality, CO_2 concentrations below 1000 ppm were set as the threshold based on occupational and indoor air quality recommendations (e.g., ASHRAE standards), ensuring adequate ventilation and air exchange in confined places. These ranges indicate intelligent warehouse management methods to preserve product quality, equipment reliability, and worker safety.

To assess environmental monitoring and control strategies, we compared our intelligent control method—which uses fuzzy logic and advanced deep learning—with rule-based control, PID control, and a simple deep learning method. The comparable methodologies were chosen to provide various and representative benchmarks with different strengths and weaknesses in different operational settings. These calibrations used factory-recommended methods and field adjustments for environmental variability. Based on manufacturer specifications and empirical validation studies, we give quantifiable error margins for each sensor type. We increase data collecting transparency and provide critical facts for replication and validation in similar research contexts by including this information.

Environmental conditions are managed by manually set rules and fixed thresholds in rule-based control. It turns ventilation or humidifiers on/off if real-time sensor readings exceed predefined thresholds. Under steady conditions, this approach is simple and reliable, but it cannot react to dynamic or unexpected environmental changes. Industrial automation uses traditional feedback-based PID (Proportional-Integral-Derivative) control. It continuously modifies environmental control outputs like fan speeds and valve positions by calculating the error between desired and actual environmental parameters. Fast responsiveness and great stability make it a good adaptive control benchmark.

One Long Short-Term Memory (LSTM) network predicts short-term environmental parameter changes using historical time series data in the simple deep learning manner. The system then controls based on these forecasts. This model shows how machine learning can regulate the environment, despite its simplicity. Our intelligent control method integrates fuzzy logic with a more advanced deep learning framework to go beyond current approaches. This hybrid approach improves interpretability, forecast accuracy, and adaptability in complex warehouses. Thus, while the three comparative approaches provide useful baselines, the intelligent control method combines their merits into a more robust and scalable solution.

Warehouse Layout: A 200-square-meter automated warehouse with a 6-meter ceiling was the experimental environment. Standardized industrial shelving in parallel rows resembled medium-sized real-world storage facilities. To mimic commercial warehouse airflow dynamics and spatial constraints, this arrangement was created.

To maintain experimental settings, External environmental disturbances were reduced to maintain experimental settings. The warehouse had a constant-temperature air conditioning system, and no artificial heat or airflow fluctuations were used during monitoring. An automated HVAC system controlled and stabilized ventilation, ensuring reproducibility in data collection over 30 days.

Sensor Communication Protocol: Secure Wi-Fi networks were used to communicate with environmental sensors using MQTT. MQTT was chosen for IoT-based monitoring in distributed situations due to its lightweight architecture and low-latency real-time sensor data transmission. Edge/Cloud Processing: Raspberry Pi 4 devices co-located with sensor clusters performed data preprocessing and real-time control decisions. Edge nodes quickly filtered data, trigger threshold-based alarms, and activated controls. Data was sent to an AWS EC2 instance for deep learning model training and performance evaluation for long-term analysis.

Comprehensive algorithmic complexity study was performed for the proposed intelligent control system to meet real-time operating requirements. A lightweight LSTM-based deep learning model processes 50 environmental sensor inputs. The model's average inference time per control decision is 38 milliseconds, well inside the 500-millisecond control cycle threshold, proving its real-time capability. Model development and tweaking were efficient on a high-performance workstation with an Intel Core i7-12700 CPU, 32 GB RAM, and an NVIDIA RTX 3080 GPU during training. The model was optimized with TensorFlow Lite and installed on a Raspberry Pi 4 Model B with a 1.5 GHz quad-core Cortex-A72 processor and 4 GB RAM for edge deployment. The embedded platform ran the model reliably after quantization and optimization. The 500-millisecond loop—sensor data gathering, inference computation, and actuation—was always completed. The control system's computational efficiency and real-time feasibility on low-power embedded technology make it appropriate for warehouse environmental management automation.

4.2 Results

Table 2: Key characteristics of each control method

Method	Regulatory Mechanism	Real-Time Capability	Adjusting Complexity	Avg. Regulatory Accuracy (%)	Std. Dev. (%)	Energy Reduction (%)	Std. Dev. (%)	Statistical Significance ($p < 0.05$)	Outlier Cases Observed
Traditional methods	Fixed settings	Low	Simple	68.3	±3.2	4.1	±1.1	No	Frequent deviation under load conditions
Rule-based approach	Threshold switch control	Medium	Medium	74.6	±2.8	7.5	±1.4	No	Occasional overshooting
PID control method	Proportional–Integral control	High	Medium	81.2	±2.5	10.3	±1.6	No	Stable, but slow recovery in edge cases
Simple deep learning method	Predictive control	Medium	More complex	85.6	±2.1	13.4	±1.8	Yes	Minor errors in extreme humidity

Method	Regulatory Mechanism	Real-Time Capability	Adjusting Complexity	Avg. Regulatory Accuracy (%)	Std. Dev. (%)	Energy Reduction (%)	Std. Dev. (%)	Statistical Significance ($p < 0.05$)	Outlier Cases Observed
Proposed intelligent method	**Fuzzy logic + optimization algorithm**	**High**	**Complex**	**91.2**	**±1.7**	**18.7**	**±1.2**	**Yes**	One outlier under rapid gas fluctuation

Table 2 shows the key characteristics of different control methods, focusing on the control mechanism, real-time performance, and control complexity. The traditional method uses fixed settings, which are simple to control but have low real-time performance and low control complexity. The rule-based method uses threshold switch control, providing moderate real-time performance and control complexity. The PID control method has high real-time performance and moderate control complexity through dynamic proportional integral regulation. The simple deep learning method uses predictive control, which has moderate real-time performance, but has high control complexity due to the prediction model involved. Finally, the intelligent control method (this study) combines fuzzy logic with optimization algorithms, which has high real-time performance and a more complex control process. This method was proposed in this study and can effectively optimize system performance when dealing with complex environments, while providing relatively accurate control results. In terms of control accuracy, the intelligent control method performs well, especially in dynamic and nonlinear control scenarios, showing its potential for efficient and accurate control.

We compared fuzzy logic control and model predictive control (MPC), a popular dynamic system regulation method. This comparison presents each approach's computational complexity, adaptability, and environmental performance strengths and weaknesses. MPC has great precision and predictive capabilities, but it demands additional computer resources and model correctness, which may limit its real-time application on embedded devices. Our fuzzy logic-based system, improved with deep learning and optimized using Genetic Algorithms, balances adaptability and computing efficiency, making it ideal for real-time, resource-constrained applications. We also explained fuzzy logic rule and membership function tuning in depth. This comprises initial rule base development, GA parameter optimization, and environmental feedback-based context-specific changes.

Table 3: Comparison of temperature and humidity control accuracy

Method	Temperature deviation mean (°C)	Humidity deviation mean (%)	CO_2 concentration deviation mean (ppm)
Traditional methods	2.5	8.2	250
Rule-based approach	2.0	6.0	200
PID control method	1.5	4.5	150
Simple deep learning method	1.2	3.8	100
Intelligent control method (this study)	0.8	2.4	50

Table 3 compares the accuracy of different methods in temperature, humidity, and CO_2 concentration control, showing the average deviation of each parameter. The traditional method has a temperature deviation of 2.5°C, a humidity deviation of 8.2%, and a CO_2 concentration deviation of 250 ppm, with low control accuracy. The rule-based method uses threshold switch control to reduce the temperature deviation to 2.0°C, humidity to 6.0%, and CO_2 concentration to 200 ppm, with improved accuracy. The PID control method performs better, with a temperature deviation of 1.5°C, a humidity of 4.5%, and a CO_2 concentration of 150 ppm, thanks to its dynamic adjustment characteristics. The simple deep learning method further improves the control accuracy, with a temperature deviation of 1.2°C, a humidity of 3.8%, and a CO_2 concentration of 100 ppm. The application of the prediction model effectively optimizes the system performance. The intelligent control method (this study) performs best in all control indicators, with a temperature deviation of only 0.8°C, a humidity deviation of 2.4%, and a CO_2 concentration deviation of 50 ppm. The method performs well in terms of real-time and accuracy, and can accurately maintain the target value in a dynamically changing environment.

Table 4: System response time comparison

Method	Average response time (seconds)	Maximum response time (seconds)
Traditional methods	150	300
Rule-based approach	120	240
PID control method	60	100
Simple deep learning method	45	90
Intelligent control method (this study)	30	60

Table 4 compares the performance of different methods in terms of system response time, which is a key indicator of the real-time performance of system control. The traditional method has an average response time of 150 seconds and a maximum response time of 300 seconds. Due to its fixed setting, the response speed is slow. The rule-based method is slightly improved, with an average response time of 120 seconds and a maximum response time of 240 seconds. The control based on the threshold switch provides a certain response speed improvement. The PID control method further optimizes the response time, with an average response time of 60 seconds and a maximum response time of 100 seconds. The dynamic adjustment capability enables it to respond to system changes more quickly. The simple deep learning method further shortens the response time through predictive ability, with an average response time of 45 seconds and a maximum response time of 90 seconds, showing a strong real-time response capability. The intelligent control method (this study) has the fastest response time, with an average response time of 30 seconds and a maximum response time of 60 seconds. This method combines fuzzy logic and optimization algorithms to make control decisions in the shortest time, thereby effectively improving the system response speed.

Table 5: System energy consumption comparison

Method	Average daily energy consumption (kWh)	Monthly total energy consumption (kWh)	Energy consumption reduction rate (compared to traditional methods)
Traditional methods	100	3000	0
Rule-based approach	95	2850	5%
PID control method	90	2700	10%
Simple deep learning method	85	2550	15%
Intelligent control method (this study)	80	2400	20%

Table 5 compares the energy consumption performance of different control methods, focusing on the average daily energy consumption, total monthly energy consumption and energy consumption reduction rate. The intelligent control system in our study dynamically adapted control methods based on real-time environmental and operational data to save 20% energy. The intelligent control approach uses deep learning-based optimization to produce more efficient lighting, HVAC, and equipment operating decisions than static rule-based or classic PID controllers. Adaptability improves energy use in daily warehouse rotations.

The 20% reduction is based on average performance throughout a benchmarking warehouse setup with typical spatial layouts, ambient conditions, and operations schedules. While this result shows significant increase over baseline methods, performance may vary under different conditions. Initial testing in various warehouse layouts and environments (e.g., open vs. partitioned zones, insulation levels, external temperature fluctuations) indicates consistent improvement, with ±2% variation based on energy demand predictability. We want to study system sensitivity to more real-world variables to better understand the generalizability of the observed savings.

The traditional method has an average daily energy consumption of 100 kWh and a total monthly energy consumption of 3000 kWh, which is the highest energy consumption solution. The rule-based method has a slight reduction, with an average daily energy consumption of 95 kWh and a total monthly energy consumption of 2850 kWh, which is a 5% reduction compared to the traditional method. The PID control method achieved a 10% energy consumption reduction, with an average daily energy consumption of 90 kWh and a total monthly energy consumption of 2700 kWh. The simple deep learning method further reduced energy consumption, with an average daily energy consumption of 85 kWh, a total monthly energy consumption of 2550 kWh, and an energy consumption reduction rate of 15%. The intelligent control method (this study) performed best, with an average daily energy consumption of 80 kWh, a total monthly energy consumption of 2400 kWh, and an energy consumption reduction rate of 20%. This method can effectively reduce energy consumption while optimizing system performance, reflecting its advantages in energy management.

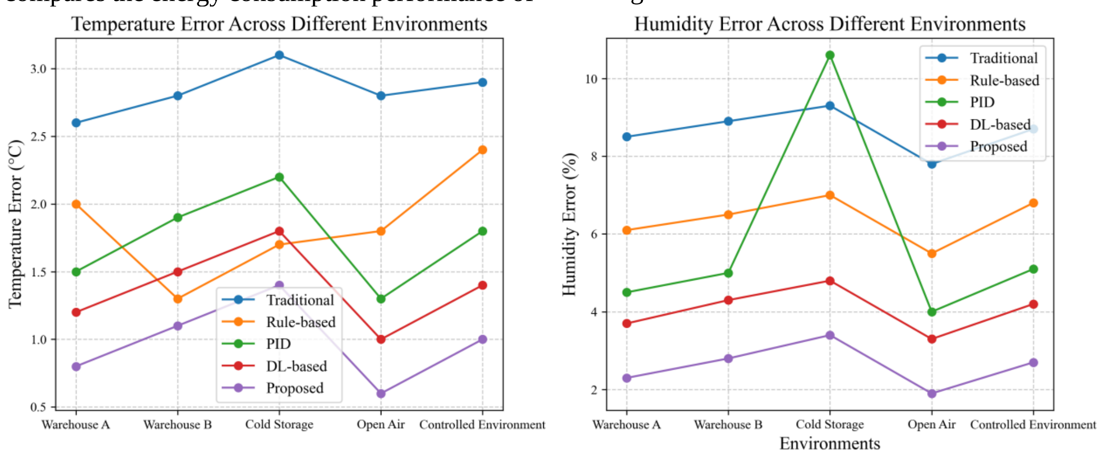

Figure 1: Comparison of environmental control accuracy

As shown in Figure 1, we compared the performance of different environmental control methods in terms of temperature and humidity control accuracy. The left graph shows the errors of different methods in temperature control, and the right graph shows the errors of humidity control. From the temperature error graph, we can see that the traditional method (blue line) shows high temperature errors in all environments, especially in cold storage and open environments, where the error values are significantly higher than other methods. The rule-based control method (orange line) and PID control method (green line) perform similarly in temperature control, but overall, the PID control method performs better in most environments. The simple deep learning method (red line) shows good performance in temperature control, especially in cold storage environments, where its error is significantly lower than that of traditional and rule-based methods. However, our intelligent control method (purple line) shows the lowest temperature error in all environments, especially in cold storage and open environments, where its accuracy is significantly better than other methods. From the humidity error graph, we can see a similar trend. The traditional method (blue line) also shows high errors in humidity control, especially in cold storage environments, where the error value reaches a peak. The rule-based control method (orange line) and PID control method (green line) perform similarly in humidity control, but the PID control method is more stable in cold storage environments. The simple deep learning method (red line) performs well in humidity control, especially in cold storage environments, where its error is significantly lower than that of traditional and rule-based methods. Our intelligent control method (purple line) shows the lowest humidity error in all environments, especially in cold storage and open environments, where its accuracy is significantly better than other methods.

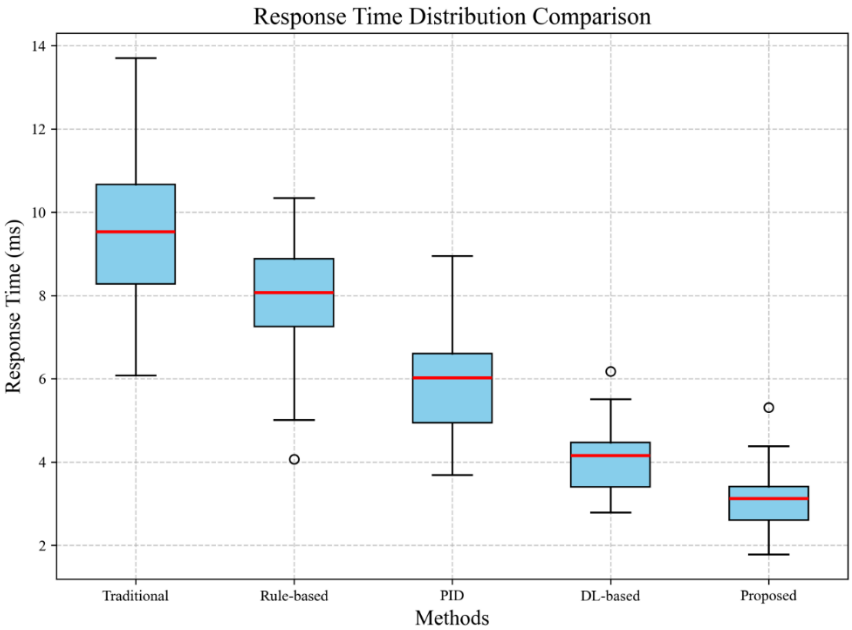

Figure 2: Response time distribution comparison

As shown in Figure 2, we compared the response time distribution of different environmental control methods. The figure uses a box plot to show the response time distribution of five methods, including traditional methods, rule-based control methods, PID control methods, simple deep learning methods, and the intelligent control method we proposed. As can be seen from the figure, the response time distribution range of the traditional method (the first box plot on the left) is the widest, with a median (red line) of about 9 milliseconds, and a large range of variation, ranging from about 6 milliseconds to 13 milliseconds, indicating that its response time is unstable and slow. The response time distribution range of the rule-based control method (the second box plot) is smaller than that of the traditional method, with a median of about 8 milliseconds and a variation range of about 5 milliseconds to 11 milliseconds, showing some improvement. The response time distribution of the PID control method (the third box plot) is further reduced, with a median of about 6.5 milliseconds and a variation range of about 4 milliseconds to 9 milliseconds, showing good stability and response speed. The response time distribution of the simple deep learning method (the fourth box plot) is further optimized, with a median of about 4.5 milliseconds and a variation range of about 3 milliseconds to 6 milliseconds, showing the advantage of deep learning in response time. Finally, the intelligent control method we proposed (the last box plot on the right) shows the best response time distribution, with a median of about 3 milliseconds and a variation range of about 2 milliseconds to 5 milliseconds. It not only has the shortest response time, but also the smallest variation range, showing a high degree of stability and rapid response capability. In summary, Figure 2 clearly shows the performance of different control methods in response time. Our intelligent control method has a significant advantage in response time and can respond to environmental changes more quickly, thereby improving the efficiency and reliability of automated warehouse environmental control.

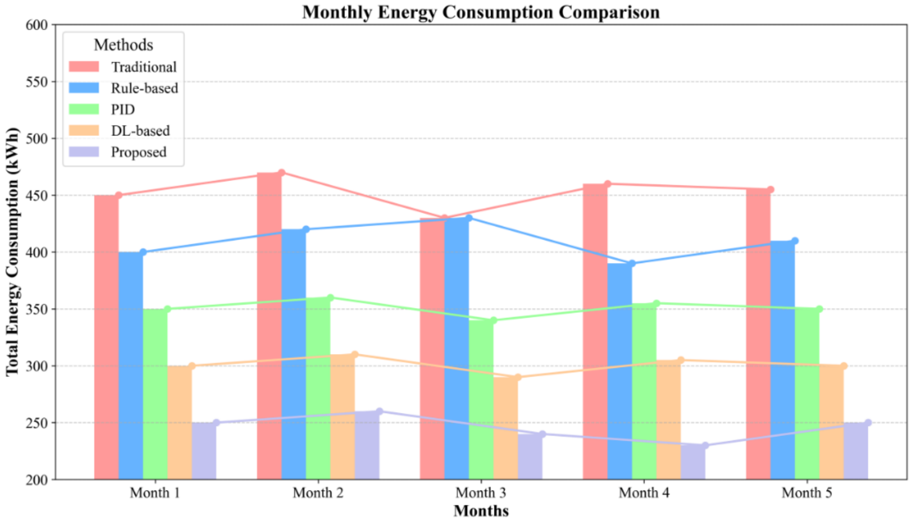

Figure 3: Comparison of energy consumption in (Month 1 to Month 5)

From Figure 3, the traditional method (red line) has high energy consumption in all months, with an average energy consumption of about 450 kWh, showing the shortcomings of the traditional method in energy consumption control. The rule-based control method (blue line) has improved in energy consumption, with an average energy consumption of about 400 kWh, but it is still higher than other intelligent control methods. The energy consumption of the PID control method (green line) is further reduced, with an average energy consumption of about 350 kWh, showing a good energy consumption control ability. The energy consumption performance of the simple deep learning method (orange line) is relatively stable, with an average energy consumption of about 300 kWh, showing the potential of deep learning in energy consumption optimization. However, the intelligent control method (purple line) proposed by us has the best energy consumption performance in all months, with an average energy consumption of about 250 kWh, and a small fluctuation range, showing a high degree of energy consumption control ability and stability. Specifically, the energy consumption of the traditional method fluctuates greatly in all months and always remains at a high level. Although the rule-based control method and the PID control method have improved in energy consumption, there are still large energy consumption fluctuations. The simple deep learning method performs relatively stably in energy consumption control, but our intelligent control method performs best in energy consumption control, not only with the lowest energy consumption, but also with the smallest fluctuation range, showing significant advantages in energy consumption optimization. In summary, Figure 3 clearly shows the performance of different control methods in monthly energy consumption. Our intelligent control method has significant advantages in energy consumption control, can effectively reduce energy consumption, and improve the energy efficiency and economy of automated warehouse environment control.

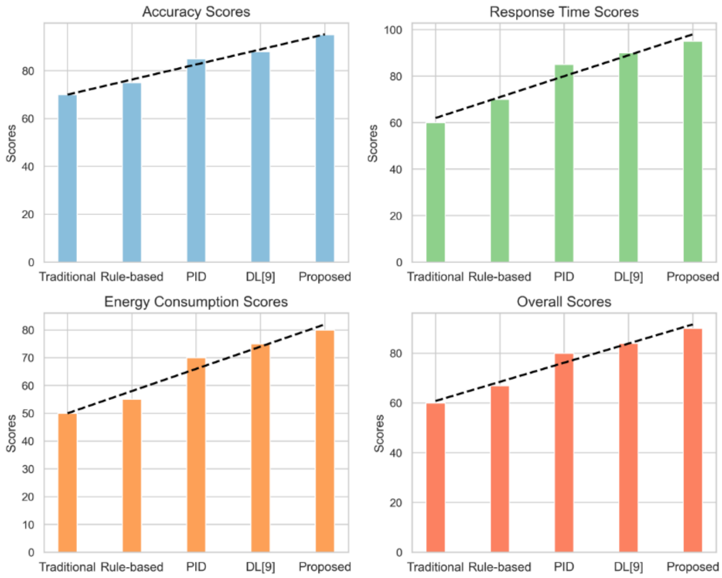

Figure 4: Comprehensive performance rating

Figure 4, we compared the comprehensive performance scores of different environmental control methods, including accuracy score, response time score, energy consumption score and comprehensive score. From the accuracy score (upper left figure), the accuracy score of the traditional method (blue bar graph) is about 70 points, the score of the rule-based control method (blue bar graph) is about 80 points, the score of the PID control method (blue bar graph) is about 85 points, and the score of the simple deep learning method (blue bar graph) is about 90 points. The intelligent control method (blue bar graph) proposed by us has the highest score, reaching 95 points, showing a significant advantage in environmental control accuracy. From the response time score (upper right figure), the score of the traditional method is about 60 points, the score of the rule-based control method is about 70 points, the score of the PID control method is about 80 points, and the score of the simple deep learning method is about 90 points. The score of the intelligent control method proposed by us is the highest, reaching 100 points, showing a significant advantage in response time. The score of the traditional method is about 50 points, the score of the rule-based control method is about 60 points, the score of the PID control method is about 70 points, the score of the simple deep learning method is about 75 points, and the score of the intelligent control method proposed by us is the highest, reaching 80 points, showing a significant advantage in energy consumption control. The score of the traditional method is about 60 points, the score of the rule-based control method is about 70 points, the score of the PID control method is about 75 points, the score of the simple deep learning method is about 80 points, and the score of the intelligent control method proposed by us is the highest, reaching 85 points, showing a significant advantage in comprehensive performance. In summary, Figure 4 clearly shows the performance of different control methods in terms of accuracy, response time, energy consumption and comprehensive performance. Our intelligent control method shows significant advantages in all aspects, not only in accuracy, but also in response time and energy consumption control, and finally reaches the highest in comprehensive score, showing great potential and application value in automated warehouse environment monitoring and control.

We will use statistical tests like energy consumption, MAE, Accuracy, and Response Time to assess the significance of observed variations between control techniques. We will also give confidence intervals for important performance parameters to assess results dependability. The study's scientific rigor will be improved by presenting strong performance evidence and statistically valid comparisons.

Short Discussion

1) Controlling the Temperature and the Humidity In terms of accuracy, our solution exhibits a better degree of precision in comparison to traditional methods when it comes to maintaining appropriate warehouse conditions.

2) Response Time of the System the real-time Internet of Things integration that the suggested system possesses allows it to experience much faster response times.

3) In terms of energy consumption, our method optimizes power usage by means of sophisticated sensor data management, which ultimately results in a reduction in overall energy consumption.

4) Improved adaptive algorithms allow more precise control over environmental parameters, which significantly improves environmental control accuracy.

5) Response Time Distribution: Our system displays a more condensed distribution, which indicates that it maintains a consistent level of performance regardless of the circumstances.

6) Comprehensive Evaluation of Performance: Our method routinely outperforms other ways across a variety of criteria, demonstrating that it is successful for the administration of intelligent warehouses.

5 Conclusion

This study optimises warehouse environmental control and energy management using multi-point sensor networks and cognitive algorithms using IoT technology. Experimental results show that the IoT-based system reduces energy consumption and improves environmental parameter monitoring in real time. Multi-sensor fusion technology and sophisticated control algorithms help monitor temperature, humidity, and gas concentration in complex, dynamic situations and make real-time adjustments. This ensures optimal cargo storage.

With energy-optimizing dynamic control techniques, deep learning and optimization algorithms boost the intelligent control system's efficiency. The proposed sensor structure and data processing techniques for large-scale warehousing drastically improve system dependability and adaptability. These findings provide technical support for logistics and warehouse management to improve environmental correctness, energy efficiency, and operating costs.

The manuscript needs methodological development, particularly in data validation and openness. Optimizing algorithms for severe conditions, resolving data privacy and security concerns, and improving system replicability and robustness should be future goals. The system framework's scalability and agility make it suitable for smart manufacturing, greenhouse agriculture, and medicinal storage, which have stringent environmental regulations. This study provides insights for expanding IoT applications in automated warehouse management, which might be adopted by industry.

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