

Scalable and Affordable IoT-based Inventory Control with Real-Time Monitoring for Small and Medium Enterprises

Vina Sari Yosephine^{1*}, Marco Batara², Marla Setiawati³

¹⁾ Industrial Engineering Department, Universitas Pembangunan Nasional Veteran Jakarta
Jl. Limo Raya, Depok, Indonesia

²⁾ Industrial Engineering Department, Institut Teknologi Harapan Bangsa
Jl. Dipatiukur 80-84, Bandung, Indonesia

³⁾ Business School and Management, Institut Teknologi Bandung
Jl. Ganesha No. 10, Bandung, Indonesia

Email: vyosephine@upnvj.ac.id

*Corresponding author

Abstract: Small and medium enterprises (SMEs) often struggle to adopt advanced inventory management systems due to high implementation costs and infrastructure complexity—barriers that are especially challenging in the context of Industry 4.0. This paper presents a scalable and affordable IoT-based stock monitoring and control system designed for small and medium enterprises. The proposed system integrates low-cost microcontrollers with ultrasonic sensors, enabling real-time stock tracking while reducing hardware expenses and complexity. Unlike existing solutions, it leverages a modular architecture for seamless scalability across different inventory sizes and environments. The system is validated through compliance with the Industry 4.0 Maturity Index and the ISA-95 standard, demonstrating its suitability for digital transformation in SME operations. Performance evaluation shows an accuracy rate exceeding 98% and response times under 10 seconds, ensuring reliable operation under varying environmental conditions. A comparative cost analysis highlights significant savings compared to conventional automated inventory systems. This approach provides an accessible entry point for SMEs seeking to enhance inventory visibility, operational efficiency, and readiness for Industry 4.0 integration.

Keywords: IoT-based inventory control, SMEs, real-time stock monitoring, low-cost scalable automation.

Introduction

In the era of Industry 4.0, businesses are experiencing rapid transformation due to advancements in artificial intelligence (AI), the Internet of Things (IoT), big data, and robotics [1], [2]. These technologies enhance efficiency and automation as well as enable real-time decision-making. For instance, modern manufacturing increasingly relies on digital transformation to achieve accurate and efficient inventory management [3], [4], [5]. Technologies like IoT sensors constantly monitor stock levels, while AI-driven systems forecast demand and automate replenishment, reduce human error, and enhance productivity.

While large enterprises have adopted these technologies, small and medium enterprises (SMEs), including micro-businesses, particularly in developing countries like Indonesia, face significant challenges in this digital transition [6], [7], [8]. The high costs related to Radio Frequency Identification (RFID) systems, barcode infrastructure, and enterprise software, along with the need for technical expertise, hinder SMEs from implementing advanced inventory solutions [9]. As a result, many SMEs continue to rely on manual inventory processes, leading to increase the risk of out-of-stocks, overstocks, and operational inefficiencies [10]. Studies highlight that readiness for Industry 4.0 among Indonesian manufacturing companies and SMEs is influenced by factors like machine book value, labor costs, revenue metrics, managerial capabilities, and technological adoption—underscoring the need for scalable and cost-effective solutions tailored to SMEs [11], [12].

To address this challenge, this paper presents a low-cost, scalable inventory management system that leverages sensors and microcontrollers to monitor stock levels real-time. Unlike RFID or barcode systems, the proposed solution does not require item-level identification but instead focuses on quantity-based detection suitable for shelf-level inventory monitoring. Its modular design allows flexible deployment across various shelf types, making it highly adaptable for SMEs with limited infrastructure.

This research evaluates the system's broader contribution to SME digital transformation. The system's capabilities are benchmarked using the Industry 4.0 Maturity Index and ISA-95 model, which assess digital readiness and integration within operational processes. Through performance tests and comparative analysis, the study highlights how affordable IoT systems serve as practical enablers for SMEs to transition from manual to semi-automated operations.

Literature Review

Small and medium enterprises contribute significantly to global economies but often face challenges in adopting advanced inventory management technologies due to financial constraints and a lack of technical expertise [7]. These challenges hinder their ability to compete with larger enterprises already embracing digital transformation. Consequently, SMEs frequently rely on manual processes, resulting in inefficiencies and inaccuracies that impede growth and profitability.

The RFID technology offers one of the most advanced inventory management solutions. The technology enables automated and real-time stock tracking [9], [13], [14]. Larger enterprises have widely adopted it because it can provide accurate data on stock movements and reduce reliance on manual labor. RFID systems consist of tags attached to products and readers that capture data remotely, even when products are not within the direct line of sight, making them suitable for complex inventory environments.

However, the high costs associated with RFID technology present a significant barrier for SMEs. Implementing RFID involves the expenses of tags, readers, and specialized software, and the ongoing maintenance costs. According to a report, the average RFID implementation is still expensive for mid-sized businesses [15], therefore it is an impractical investment for many SMEs. This financial burden, coupled with the need for technical expertise to manage the system, has limited the adoption of RFID among smaller enterprises. Despite its potential to enhance inventory management, RFID's cost-prohibitive nature has driven research to seek more affordable alternatives.

Barcode systems represent a more accessible technology for SMEs as they provide a cost-effective inventory tracking method [16]. Barcodes have been widely adopted in various industries due to their simplicity. Each product is assigned a unique code that can be scanned to monitor inventory levels. Compared to RFID, barcodes are inexpensive to implement, requiring only printed labels and basic scanning equipment. This affordability has made them a popular choice for SMEs, particularly those with limited budgets.

Despite these advantages, barcode systems are not without limitations. The need for manual scanning can be time-consuming and prone to human error, especially in environments with extensive inventories or frequent stock movements. Additionally, barcodes require a direct line of sight for scanning, limiting their efficiency in more complex or high-volume settings. Furthermore, Quick Response (QR) codes offer a slight improvement by storing more data and being compatible with smartphones, eliminating the need for dedicated scanners [17]. However, like barcodes, QR codes still rely on manual scanning, preventing them from providing real-time inventory visibility, which is crucial for optimizing stock levels and ensuring timely replenishment. Other technologies such as the weight-based systems use load cells or pressure sensors to monitor inventory by tracking changes in weight. These systems are particularly effective for businesses that handle bulk materials, such as food manufacturers or chemical processors, as they offer real-time monitoring without requiring individual product scanning. Weight-based solutions can reduce the need for manual counting, thereby minimizing errors and improving efficiency.

However, the cost of implementing weight-based systems and the need for regular calibration and maintenance can be prohibitive for SMEs. Additionally, this method may be less effective for businesses dealing with lightweight items, where minor weight changes might go undetected. As a result, despite its advantages, the weight-based limitations in terms of cost and applicability restrict its suitability for smaller enterprises with diverse inventory types. Smart shelves have gained popularity in larger retail environments, using pressure sensors to detect when items are added or removed [17]. The system offers real-time inventory updates. Major retailers like Amazon and Walmart often use this technology to ensure products are always in stock, triggering automatic reordering when inventory falls below a set threshold. However, the sophisticated infrastructure and high costs associated with smart shelves make them less accessible for SMEs. The complexity of installation,

maintenance requirements, and the need for specialized knowledge further deters smaller businesses from the adoption of this solution.

Bluetooth Low Energy (BLE) beacons provide a wireless way to track inventory by transmitting signals to nearby devices, enabling real-time stock tracking without direct contact [18]. BLE beacons offer a more affordable option than RFID, as they consume less power and require minimal infrastructure. However, signal interference can hinder their effectiveness, particularly in environments with metal obstructions, and they are more suitable for tracking larger items rather than providing precise stock level monitoring.

On the other hand, infrared (IR) sensors offer a simple and low-cost solution by detecting the presence or absence of items through infrared light reflection [19]. This makes IR sensors suitable for settings where basic stock presence detection is sufficient, such as automated vending machines. However, they lack the precision and scalability required for comprehensive inventory management, especially for SMEs with diverse product ranges or fluctuating stock levels. Environmental factors, such as dust or changes in lighting, can also affect the accuracy of IR sensors, limiting their reliability.

While each inventory management technology offers unique advantages, its cost, scalability, and complexity limitations often prevent SMEs from fully adopting it. The table below summarizes these technologies' key strengths and weaknesses, highlighting SMEs' ongoing challenges in achieving efficient, real-time inventory management.

Table 1 Technologies comparison for inventory management

Solution type	Advantages	Limitations
RFID-based systems [13], [20]	Real-time, automated tracking	High implementation and maintenance costs Requires tags for every item, increasing the cost per unit Complex infrastructure, not feasible for SMEs
Barcode systems [16]	Low cost Easy to implement	Requires manual scanning Prone to human error No real-time updates
QR code systems [16]	Stores more data than barcodes Scannable via smartphones	Requires manual scanning No real-time monitoring Limited to line-of-sight scanning
Weight-based inventory systems [17]	Real-time stock monitoring for bulk items	High cost Ineffective for lightweight or small items Requires regular calibration
Smart shelves with pressure sensors [17]	Automated stock tracking system Real-time updates	Expensive setup Suited for large-scale operations, not SMEs Requires specialized maintenance
Bluetooth low energy (BLE) beacons [18]	Low-cost, wireless tracking	Susceptible to signal interference Best for large item tracking, Not for precise stock level monitoring
Infrared sensors [19]	Simple and affordable solution	Limited to basic stock presence detection Affected by environmental factors Lacks precision
Ultrasonic sensors (This Study)	Low-cost and easy to deploy real-time stock level estimation modular and adaptable to various shelf sizes	Cannot identify specific items Accuracy affected by object shape or reflective surface Limited to bulk-level monitoring (not item-level)

Our previous research, including work by other researchers, explored the use of one ultrasonic sensor per microcontroller for real-time inventory tracking on individual shelves [21]. This approach provided an affordable alternative to expensive systems like RFID, smart shelves, and weight-based inventory systems. However, the need for a separate microcontroller for each sensor limited scalability and increased hardware costs, particularly in setups with multiple shelves. Although this method was effective for small-scale implementations, its complexity and expense grew with the size of the inventory, presenting challenges for SMEs with limited resources.

Building on the limitations identified in previous research, this study introduces an improved system configuration that utilizes one microcontroller to manage multiple ultrasonic sensors on a single shelf. The

system cuts costs and improves scalability for small and medium enterprises by reducing the hardware needed. Furthermore, the success of this new configuration relies heavily on developing a well-designed stock monitoring and control system to support the hardware.

This study addresses hardware efficiency and emphasizes the need to integrate software solutions to process and manage the increased data from multiple sensors. The stock monitoring and control system is critical in ensuring the collected data is processed accurately and in real-time. Custom-designed software is required to handle key functions such as: Data collection from multiple sensors. Real-time synchronization of stock levels across different shelves. User-friendly interfaces for easy access to inventory data. Alerts and notifications for stock shortages or surpluses. Automated reporting and inventory forecasting tools.

Methods

System Design and Setup

The stock monitoring and control system utilizes a combination of ultrasonic sensors, microcontroller technology, and a central database for managing inventory data. The setup enables real-time stock tracking with efficient hardware usage and wireless communication, as shown in Figure 1. This configuration was designed to closely mimic the real-world setups in SMEs' retail environments.

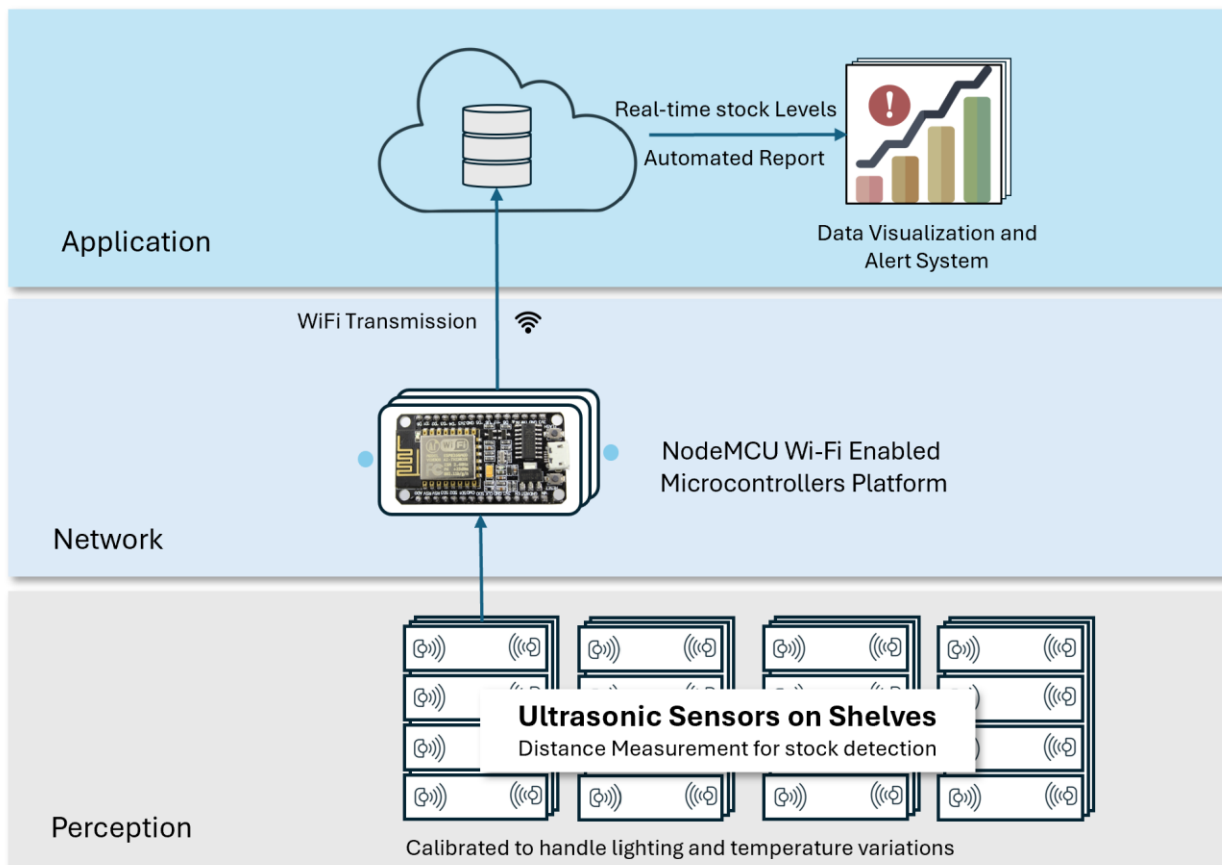


Figure 1 IoT architecture for real-time inventory monitoring system in SMEs

In this system, ultrasonic sensors capture stock data from shelves, and microcontrollers process this data. These microcontrollers were chosen for their cost-effectiveness and ability to manage multiple sensors, making them ideal for SMEs. The NodeMCU's integrated Wi-Fi capability allows data to be transmitted wirelessly to the central database, eliminating physical connections. The central database logs real-time sensor updates, enabling users to monitor stock levels, generate reports, and receive alerts for critical changes. The user-friendly interface provides inventory management from any connected device and offers convenient control. The details are described in the following sections.

Hardware Setup

The system prototype was implemented using a three-tier shelf structure, simulating typical storage racks used by small and medium enterprises (SMEs). Each shelf level is equipped with an ultrasonic sensor for real-time stock-level detection. The hardware configuration is detailed as follows: (1) A steel frame *shelf* with three levels (referred to as Shelf 1, Shelf 2, and Shelf 3), each measuring 90 cm in width, 30 cm in depth, and 40 cm in height. The total structure stands at 120 cm tall. (2) Four HC-SR04 ultrasonic *sensors* were mounted at each shelf level, as shown in Figure 2. The sensors were positioned 30–35 cm above the shelf's base to enable accurate vertical distance measurement of stored items. These sensors measure the distance to the object's surface directly below, allowing the calculation of stock presence based on distance thresholds. (3) A NodeMCU ESP8266 *microcontroller* was used to collect sensor data. In the current version, each shelf level is equipped with a microcontroller to manage the sensor directly attached to it. All microcontrollers are powered through a 5V USB power distribution hub and communicate wirelessly via Wi-Fi to transmit stock data to the server. (4) Each ultrasonic sensor is directly *connected* (wired) to its corresponding NodeMCU via GPIO pins. The NodeMCUs are programmed to read the sensor values, categorize the stock level based on predefined thresholds, and send the data via HTTP to a cloud-hosted MySQL database. (5) A shared 5V USB *power* supply simultaneously powered all NodeMCUs. The compact power distribution board was positioned at the lower rack level for ease of wiring.

This modular approach allows each shelf to function independently, making the system scalable and flexible for varying inventory setups. The accompanying system photo (see Figure 3) illustrates the positioning of sensors and microcontrollers, while the data flow and processing are described in the the following section.

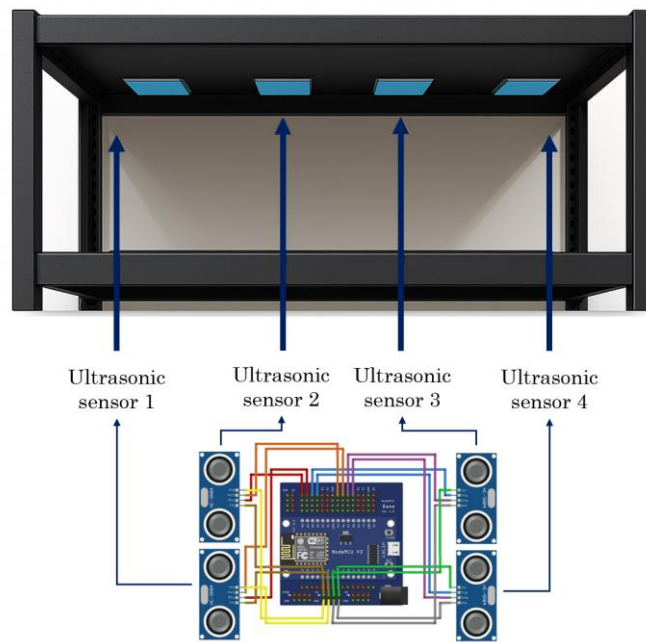


Figure 2 Ultrasonic sensor placement on shelf

Software and Programming

The NodeMCU ESP8266 microcontroller was programmed using the Arduino IDE to manage ultrasonic sensor operations, process distance readings, and transmit stock data to a web server. Each ultrasonic sensor measures the vertical distance from the top of the shelf to the surface of the object below using the time-of-flight method. The estimated time delay between the emission and reception of ultrasonic pulses is converted into the distance in centimeters using the standard speed of sound in air.

To estimate the number of items on the shelf, the measured distances are mapped to specific stock quantity values based on a threshold model developed through calibration experiments. Shorter distances correspond to fuller shelf conditions, while longer distances indicate partially filled or empty shelves. In this implementation,

distance readings between 3 and 7 centimeters are interpreted as five items (fully stocked), between 10 and 14 centimeters as four items, between 17 and 21 centimeters as three items, between 24 and 28 centimeters as two items, and between 31 and 35 centimeters as one item. Any measurement above 35 centimeters or below 3 centimeters is considered to indicate an empty shelf or invalid reading.

After the conversion, the stock quantities from all sensors points on a shelf are aggregated and transmitted to a PHP server via HTTP POST requests. The NodeMCU's built-in Wi-Fi module enables wireless communication, and updates are sent at 10-second intervals to ensure real-time data availability. The received data is stored in a MySQL database and visualized through a web-based dashboard, providing users with an accessible interface to monitor inventory status. The serial monitor was used for debugging and real-time feedback on sensor values and server communication during testing.

The software includes routines for handling sensor noise, timeouts, and network interruptions to enhance system reliability. These safeguards support stable, continuous operation, making the system suitable for small-scale inventory environments that require low-cost, autonomous solutions. This process is described as the following pseudocode shown in Table 2.

Table 2 Pseudocode of the real-time inventory monitoring system

1.	Initialize the system and connect to Wi-Fi
2.	Repeat every 10 seconds:
	a. For each sensor:
	i. Measure the distance to the object
	ii. Convert distance into discrete stock value using predefined thresholds
	b. Aggregate stock values from all sensors
	c. Transmit the total stock level to the server via HTTP request
	d. Log transmission status and wait for the next cycle
3.	End Repeat

System Integration

The proposed inventory monitoring system integrates sensor hardware, microcontroller processing, and wireless data transmission to enable real-time stock-level detection. The system operates autonomously and is designed for low-cost deployment in small-scale industrial or retail environments.

Ultrasonic sensors are installed on each shelf level to measure the vertical distance between the sensor and the surface of stored items. These sensors are connected to a NodeMCU ESP8266 microcontroller, which continuously polls the sensor data and converts the distance readings into estimated stock levels using a predefined threshold model. Each stock level is represented as a discrete quantity, corresponding to the shelf segment's full or empty.

The total stock quantity for each shelf is obtained by aggregating the readings from all sensors. This processed data is then encoded and transmitted wirelessly using HTTP POST requests to a PHP endpoint hosted on a local server. The microcontroller connects to the local Wi-Fi network and sends updates at fixed intervals, approximately every 10 seconds, ensuring the inventory data remains current.

On the server side, the received data is stored in a structured MySQL database, allowing for further retrieval, analysis, or integration into broader digital inventory systems. The overall communication flow—from sensor measurement to database storage—has been optimized for simplicity, speed, and reliability.

System diagnostics, including distance readings, stock levels, and communication status, are logged via the serial monitor during operation. This provides real-time feedback for calibration and debugging purposes. The system's modular structure enables easy expansion, allowing additional sensors or shelf units to be incorporated with minimal changes to the existing setup.

Lab-Scale Testing and Calibration

The system was tested in a lab-scale environment to simulate real-world retail SME storage conditions. As in Figure 3, three shelves were equipped with multiple ultrasonic sensors connected to a microcontroller to monitor and transmit stock levels under various conditions (fully stocked, partially stocked, and empty). Different product shapes and sizes were used to simulate typical SME inventory configurations. The system was also

calibrated under varying environmental conditions, such as changes in temperature and lighting, to ensure accurate and consistent performance.

During lab-scale testing, real-time stock-level data was collected continuously from the ultrasonic sensors. The microcontroller processed this data and transmitted it wirelessly to the central database, where stock levels were instantly updated. The system logged key metrics, such as: Stock levels. Distance measurements from sensors. Time-stamped updates to track inventory changes

This data was analyzed to evaluate the system's overall performance, focusing on detection accuracy and response time. Additionally, the system's design and performance will be assessed using the ISA-95 [22] framework and the Industry 4.0 maturity index [23]. In the subsequent analysis section, ensure that the system aligns with established industry standards and is ready for digital integration.

Results and Discussions

System Performance

The system's performance has been evaluated based on its functionality in detecting and transmitting stock levels from multiple shelves. With all hardware components, including ultrasonic sensors and the microcontroller, fully operational, the system has demonstrated high accuracy and reliability in real-time inventory management. The system has consistently detected stock levels—whether full, partially loaded, or empty. This precision is also attributed to the sensor calibration process, allowing the system to handle diverse product types and configurations with minimal errors.

The average response time remains under ten seconds, which can be considered as real-time data transmission in this configuration. The system's reliability has also been thoroughly tested across various conditions. The sensors have proven stable in detecting stock levels regardless of environmental factors, such as temperature or light intensity changes. The system has demonstrated high resilience and consistent performance over extended periods. This reliability is essential for SMEs to function seamlessly in dynamic environments. This reduction in the number of microcontrollers, combined with the system's real-time solid performance, presents a cost-effective solution.

Lab-Scale Testing Outcomes

During the testing, the system accurately measured stock levels under different configurations. In the trials where all shelves were empty, as shown in Figure 3(a), the system correctly registered stock levels as zero across all three shelves. In subsequent trials, where products were placed on the shelves in varying amounts, as shown in Figures 3(b) and 3(c), the system successfully detected the increased stock levels. Furthermore, Figure 4 shows the stock data and microcontroller programming using Arduino.



Figure 3 (a) Empty shelf (b) Partially loaded (c) Fully loaded

The ultrasonic sensors provided accurate readings, translating into reliable stock updates. The system demonstrated a fast response time, updating stock levels almost instantaneously. In all trials, the system could process stock changes and update the central system in under ten seconds. This fast response time ensures that users can access real time information on stock levels, allowing them to make quick decisions about inventory adjustments.

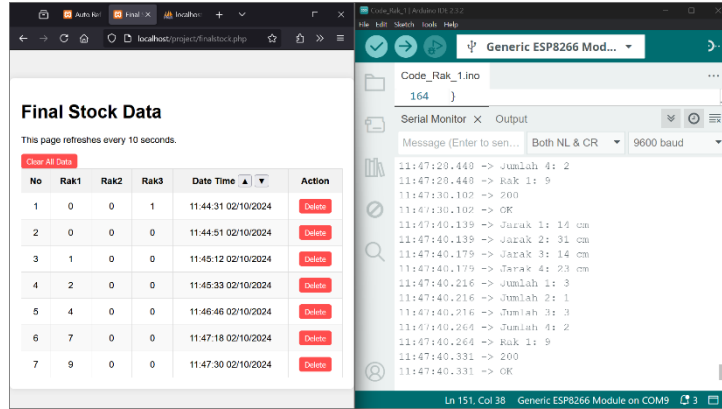


Figure 4 Database and microcontroller programming

The system maintained stable and consistent performance across all tests. The sensors accurately detected stock levels regardless of environmental factors such as room temperature or lighting. Over an extended testing period, the system continued providing real-time updates without significant performance degradation, as shown in Table 3.

Table 3. Stock detection performance for each shelf

Shelf	Test 1 (empty)	Test 2 (partially loaded)	Test 3 (fully stocked)
1	0	1	3
2	0	1	2
3	0	1	2
Total stock	0	3	7

The system's accuracy was also tested with products of different shapes and sizes. The accuracy of stock detection varied slightly depending on the product type, with regular-shaped products like boxes showing the highest accuracy rates. At the same time, irregularly shaped items had marginally lower accuracy. Table 4 summarizes each product type's mean accuracy and standard deviation.

Table 4. Stock detection performance for products with different shapes and sizes

Product type	Shape	Mean accuracy	Standard deviation
Box	Rectangular	99%	0.3%
Irregular item 1	Irregular shape 1	98%	0.5%

To address potential variability in object size within the same shape category, additional experiments were conducted using two different rectangular products: one medium-sized ($22 \times 22 \times 7$ cm) and one smaller-sized ($16 \times 16 \times 3$ cm). These experiments, previously published in a related study [21], evaluated the system's performance across repeated trials. The results demonstrated high measurement reliability, with Intraclass Correlation Coefficients (ICC) reaching 0.999 and Cronbach's Alpha values of 1.000 for both product sizes. These findings indicate that the system consistently detects stock levels accurately, regardless of object size, if the object maintains a similar reflective surface and geometric shape. Therefore, size variation within the same shape category had minimal effect on detection accuracy and was not separated into individual entries in Table 3.

Stock detection accuracy was calculated by comparing the detected stock count (based on measured distance) with the ground-truth stock level corresponding to each experimental condition. Each test was repeated multiple times across four ultrasonic sensors, resulting in over 100 individual measurements. The system used predefined distance thresholds to classify stock levels ranging from 0 (empty) to 5 (fully stocked). Detection accuracy (%) was calculated as the percentage of correct classifications over total measurements per condition using the formula:

$$\text{Accuracy \%} = \frac{\text{Number of Correct Classifications}}{\text{Total Number of Trials}} \times 100$$

For example, if 19 measured values correctly matched the expected stock category in 20 trials, the accuracy would be 95%. ICC and Cronbach's Alpha scores from previous trials further supported consistency across repeated tests.

A paired t-test was conducted to determine if the differences between regular and irregular product types were statistically significant. The test indicated a p-value < 0.05, confirming that the system's performance varies depending on product type. This suggests that although the system works well with different product shapes, minor adjustments in sensor calibration may be needed for highly irregular items. The system's stock detection performance was evaluated under varying environmental conditions, including changes in temperature and lighting. Table 5 shows how different environmental settings affect sensor accuracy.

Table 5. Stock detection performance for products under different environmental conditions

Environmental condition	Temperature	Lighting condition	Mean accuracy (%)
Room temperature	25	Normal	99%
High temperature	35	Normal	98%
Low temperature	20	Normal	99%
Normal temperature	25	Low	99%

A confidence interval of 95% was calculated for the accuracy under each condition to confirm that the system's accuracy remains within acceptable limits across all environmental conditions. However, as seen with high temperatures, a slight decrease in accuracy was observed, suggesting that additional sensor calibration might be required in extreme environments. This experiment tested the system's performance when shelves were densely and sparsely stocked. As shown in Table 6, accuracy remained relatively high in both cases, but response times were consistent.

Table 6. Stock detection performance for products with different density

Stock density	Items on shelf	Mean accuracy (%)	Response time (s)
Low density	3	98%	Max 10
High density	20	99%	Max 10

A paired t-test was conducted to compare the mean response time between high and low-density stock conditions. The result indicated that while the difference is statistically significant (p-value < 0.05), the response time remains under ten seconds, which is still well within acceptable limits for real-time monitoring. The system maintained a consistent accuracy rate of over 98% throughout the testing period, with response times staying below 1 second for most of the trial. A regression analysis was performed to predict system performance over an extended period. The result indicated that accuracy will likely remain stable for prolonged usage, with no significant performance degradation. To test the system's ability to handle concurrent stock changes, items were added or removed from multiple shelves simultaneously. The results were recorded in Table 7.

Table 7. Stock detection performance for products with different testing

Shelf	Stock change (add/remove)	Response time (s)	Detection accuracy (%)
Shelf 1	Add 3 items	Max 10	98%
Shelf 2	Remove 2 items	Max 10	99%
Shelf 3	Add 1 item	Max 10	97%

The experiment results show that the system successfully handled simultaneous changes without any significant increase in response time or reduction in accuracy, indicating strong scalability.

Cost Efficiency Evaluation

The total hardware cost for implementing the IoT-based inventory management system was approximately IDR 300,000 (around 20 USD) per shelf. This includes IDR 100,000 (6.67 USD) for the microcontroller, IDR 80,000 (5.33 USD) for four sensors (each sensor costing IDR 20,000 or 1.33 USD), and an additional IDR 100,000 (6.67 USD) for other necessary components and installations. Compared to traditional RFID systems, which can cost hundreds to thousands of USD per shelf just for the hardware, this configuration represents a significantly more affordable solution for SMEs. This cost-effectiveness further supports the system's scalability,

making it accessible to small and medium enterprises seeking to modernize their inventory management processes.

Limitations

While the proposed system demonstrates strong accuracy, responsiveness, and scalability performance, several limitations should be acknowledged. The use of ultrasonic sensors—though cost-effective—restricts the system to quantity-based stock monitoring without item-level identification. This makes it suitable for environments where bulk tracking is sufficient but not for applications requiring product traceability, such as RFID or barcode systems. Additionally, the sensor readings can be influenced by the shape and surface of the items. At the same time, box-shaped products showed high accuracy, but irregular objects may cause deflections or inconsistent distance measurements. Calibration helped mitigate these issues, but further tuning would be necessary in environments with more significant variation in object geometry or material.

The system also relies on static threshold values to convert distance into quantity estimates, which may need to be adjusted for different shelf configurations or item sizes. Furthermore, the current implementation was tested in a controlled lab setting, and real-world conditions—such as wireless interference, inconsistent placement, or fluctuating ambient conditions—could introduce challenges not yet encountered. While the system provides real-time monitoring and logging, it does not yet support advanced features like anomaly detection, historical analytics, or predictive forecasting. These could be incorporated in future iterations by integrating machine learning or computer vision. Nonetheless, the system offers a practical and scalable solution for SMEs seeking to transition toward digital inventory management with minimal cost and complexity.

Discussion

Positioning the System Among Inventory Technologies

The experiment results demonstrate that the proposed system can reliably detect stock levels using high accuracy ultrasonic sensors under various shelf conditions. However, to fully understand this system's contribution within a broader technological and strategic context, it is important to consider its position relative to other inventory-tracking technologies.

Advanced solutions such as RFID, barcode, and QR code systems offer item-level identification and traceability, essential in environments with high product variability or strict tracking requirements. These technologies enable detailed monitoring of individual products but often require significant investment in hardware, infrastructure, and system integration. Such investments may not be financially viable for small and medium enterprises (SMEs), especially those in the early stages of digital transformation.

In contrast, the developed system offers a low-cost, entry-level solution focused on quantity-level monitoring through distance-based sensing. While it does not provide product-level identification, it fills a critical gap for SMEs seeking to digitize their operations without the complexity or expense of full-scale systems. Given this positioning, the system's impact is best evaluated by its technical performance and contribution to digital maturity.

The results demonstrated that the IoT-based inventory management system improved SMEs' accuracy, response time, and reliability. Building on these findings, a deeper evaluation is necessary to understand the system's overall impact on digital integration and operational efficiency. The system is then analyzed using the Industry 4.0 maturity index and the ISA-95 model. These frameworks provide a structured perspective on how the system aligns with advanced manufacturing principles and digital transformation goals.

The Industry 4.0 maturity index offers a structured assessment across eight dimensions: technology adoption, data integration, operational automation, and corporate standards. By examining the system's progress across these dimensions, from pre-implementation to post-implementation, this analysis illustrates how the IoT-based system has enhanced inventory accuracy, labor efficiency, and customer satisfaction. It also identifies areas where further development is necessary.

Table 8. Assessment of the proposed IoT inventory system based on Industry 4.0 maturity dimensions

No	Maturity dimension	Specific metric	Before implementation		After implementation	
			Level	Justification	Level	Justification
1	Technology	Inventory Accuracy	1	No use of IoT sensors, cloud technology, or real-time monitoring. Inventory tracking was manual and prone to errors.	7	The system utilizes IoT-based sensors for real-time inventory tracking, improving data and reducing manual errors.
		Space Utilization	3	Overstocking and underutilization of space due to a lack of visibility in current stock levels.	6	Real-time data allows for better space planning and reduced overstock, though not yet fully optimized.
2	Products and Services	Stockouts Reduction	2	Stockouts were common due to manual reordering and a lack of real-time stock data.	7	Automated reordering alerts have improved stock availability, reducing the frequency of stockouts.
3	Value Creation Processes	Labor Hours	1	Manual counting and restocking required significant labor time and effort.	6	Automation has reduced the time spent on routine inventory tasks, freeing up staff for higher-value work.
		Labor Costs	2	High labor costs due to repetitive manual inventory management processes.	6	Reduced labor demand through automation results in lower operational costs.
4	Customers and Partners	Customer Satisfaction	2	Delayed reordering often leads to product unavailability and customer dissatisfaction.	6	Improved internal stock visibility ensures better product availability, indirectly increasing customer satisfaction.
5	Data and Information	Data Accuracy	1	Manual records were inconsistent and often outdated, with no real-time data sharing.	7	Real-time data updates enhance decision-making and provide a more accurate reflection of inventory conditions.
6	Employee Competencies	Digital Competencies	2	Employees lacked training in digital systems and relied on manual workflows.	5	Basic digital training has enabled staff to use the IoT system and improve digital readiness effectively.
7	Strategy and Leadership	Digital Transformation	1	No defined strategy or investment in digital inventory tools.	8	A digital roadmap has been initiated, aligning system use with broader SME modernization goals.
8	Corporate Standards	Digital Standards	1	No cybersecurity or digital process standards were in place.	5	Basic digital protocols and standard operating procedures have been introduced, providing a foundation for future improvements.

In parallel, the ISA-95 model, originally designed to integrate enterprise and control systems in manufacturing environments, to provide a structured approach to understanding how the IoT-based inventory management system aligns with operational and business processes. Mapping the system's impact across different ISA-95 levels, from real-time operations management to business planning, allows this analysis to demonstrate how the system bridges the gap between warehouse operations and enterprise resource planning (ERP). This mapping offers insights into how the system enhances data flow, operational efficiency, and decision-making, aligning with Industry 4.0 principles.

Industry 4.0 Maturity Index

The maturity index uses a scale from 1 to 10 to evaluate the system's performance across various metrics. Level 1 represents minimal or no implementation of Industry 4.0 technologies, characterized by manual operations

prone to inefficiencies and errors. At this stage, inventory management involves manual stock counts, lacking any form of automation. As organizations progress through the levels, the degree of automation and technology integration increases. By Level 5, some digital tools or sensors are present, but manual oversight remains significant. Levels 7 to 9 reflect advanced automation, where IoT systems, real-time data collection, and integrated decision-making tools substantially reduce human intervention, improving accuracy, efficiency, and responsiveness. Level 10 represents a fully automated, self-regulating state, with little to no manual input required, marking the pinnacle of digital integration and automation.

The proposed system's affordability aligns with the financial constraints typically faced by SMEs. With a total hardware cost of approximately 20 USD per shelf, the system offers a substantial reduction compared to RFID-based solutions, allowing SMEs to advance their inventory management processes without significant financial barriers. This cost efficiency supports the Technology and Strategy dimensions of the Industry 4.0 maturity index. It contributes to the value creation process, enabling SMEs to adopt digital inventory management without compromising their budget.

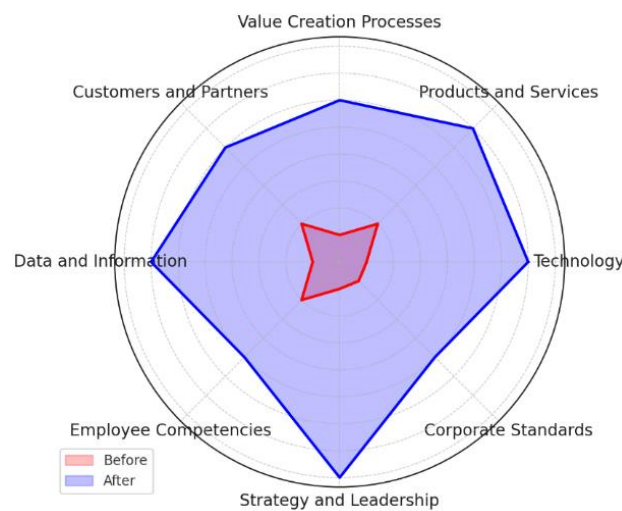


Figure 5 Industry 4.0 maturity index analysis summary

ISA-95

The ISA-95 model analyzes the integration of enterprise and operational systems in modern industrial processes. Initially designed for manufacturing, ISA-95 structures the flow of information from the physical production floor to business planning and logistics, spanning five levels. The model standardizes communication and data flow between these levels, ensuring production aligns with broader business objectives.

Table 9 Functional Mapping of the Proposed IoT-Based Inventory Monitoring System to ISA-95 Levels

ISA-95 level	Functional level	System capability	Explanation
Level 0	Physical process	Stock presence detection	Ultrasonic sensors measure the physical item presence and distance on shelves.
Level 1	Sensing and manipulation	Data acquisition from sensors	Distance data is collected in real-time to estimate stock levels.
Level 2	Monitoring and control	Microcontroller-based processing and alerting	NodeMCU processes stock levels and sends alerts when the stock drops below a threshold.
Level 3	Manufacturing operations management	Reordering alerts and dashboard monitoring	Stock data is used to trigger replenishment notifications and update inventory logs.
Level 4	Business planning and logistics	Data integration with enterprise systems (future potential)	Although basic for now, the system structure allows future integration with ERP for inventory planning.

The IoT-based system developed for SMEs was evaluated using the ISA-95 framework to understand how it improves real-time data collection, inventory management, and the integration of warehouse operations with business systems. The analysis focuses on Level 3, Manufacturing Operations Management, and 4, Business Planning and Logistics. By leveraging real-time data, the system facilitates the connection between operational

activities (such as stock tracking) and higher-level functions (such as demand forecasting and procurement), aligning with the principles of ISA-95 to enhance decision-making and overall business performance.

The IoT-based inventory management system for SMEs has markedly improved operational efficiency and digital maturity. For instance, at ISA-95 Levels 0 and 1, Physical Processes and Sensing, the system transitioned from manual inventory processes to real-time IoT sensor monitoring. This also aligns with the Technology dimension of the Maturity Index, reaching Level 7 for automated sensing and tracking. At ISA-95 Level 2, Monitoring and Supervisory Control, the system incorporated real-time dashboards and alerts, enhancing decision-making by delivering automated stock notifications. This corresponds to Level 7 in the Data and Information dimension of the Maturity Index, indicating enhanced data flow and accuracy.

The system facilitates manual reordering based on automated alerts at ISA-95 Level 3. Although reordering is not entirely automated, these alerts streamline stock control, contributing to improved Value Creation Processes (Level 6 in the Maturity Index). At ISA-95 Level 4, the system integrates with a customized information system, supporting basic business planning and logistics, which elevates the Strategy and Leadership dimension to Level 8.

The system also enhances the Products and Services dimension by improving product availability through real-time monitoring, achieving Level 7. While direct data sharing with customers is not implemented, internal alerts have improved customer service, elevating the Customers and Partners dimension to Level 6. Regarding Employee Competencies, basic training has enabled staff to utilize the system effectively, raising this dimension to Level 5. Corporate Standards are currently at Level 5, with basic digital security protocols established, though further improvements are planned.

While the current system focuses on quantity-based inventory monitoring, future enhancements could include integrating low-cost computer vision modules to enable basic item identification. For example, webcams paired with lightweight image classification models could help verify product types based on shape, color, or packaging features. Although such an approach would not achieve the precision of RFID, it offers a cost-effective alternative for SMEs unable to afford complete traceability systems. Additionally, hybrid configurations combining ultrasonic sensing with barcode or QR code scanning could extend the system's capabilities without significant hardware complexity. These enhancements would allow the system to evolve from bulk-level monitoring toward semi-automated item recognition, bridging the gap between affordability and functionality in SME contexts.

Conclusion

This research developed a scalable and cost-effective IoT-based inventory management system tailored to the needs of small and medium enterprises. The system's implementation using ultrasonic sensors, microcontroller technology, and a central database has addressed the key challenges SMEs face in adopting advanced inventory solutions, such as high costs, limited automation, and reliance on manual processes.

The system demonstrated high accuracy through lab-scale testing, with over 98% precision in detecting stock levels across various product types and sizes. It also maintained real-time responsiveness, with average response times below one second, ensuring timely and reliable inventory updates. The system's ability to operate effectively under different environmental conditions and product configurations validated its potential as a practical solution for SMEs seeking to modernize their inventory management processes.

The analysis using the Industry 4.0 maturity index and the ISA-95 model confirmed the system's alignment with advanced manufacturing principles, showcasing its readiness for digital integration and capability to bridge the gap between operational activities and higher-level business planning. Integrating the system with enterprise resource planning further demonstrated how SMEs could leverage IoT technologies to enhance data flow, decision-making, and overall operational efficiency.

While this research has shown promising results, opportunities exist to enhance the system further. Incorporating machine learning algorithms to analyze inventory data and predict stock levels could significantly improve the system's accuracy and adaptability. Using machine learning to confirm and refine sensor readings, the system could better handle irregularly shaped products, environmental variations, and dynamic inventory

patterns. This enhancement would increase inventory accuracy and provide SMEs with predictive insights for more efficient stock management, further aligning the system with Industry 4.0 principles.

References

- [1] L. Barreto, A. Amaral, and T. Pereira, "Industry 4.0 implications in logistics: An overview," *Procedia Manufacturing*, vol. 13, pp. 1245–1252, Jan. 2017, doi: <https://doi.org/10.1016/j.promfg.2017.09.045>.
- [2] J. Lee, B. Bagheri, and H.-A. Kao, "A cyber-physical systems architecture for Industry 4.0-based manufacturing systems," *Manufacturing Letters*, vol. 3, pp. 18–23, Jan. 2015, doi: <https://doi.org/10.1016/j.mfglet.2014.12.001>.
- [3] N. Rani, M. K. Sharma, S. Kathuria, N. Yamsani, S. V. Akram, and R. Balyan, "Revolutionizing inventory management: The role of IoT in inventory management 4.0," presented at the 2024 *3rd International Conference on Sentiment Analysis and Deep Learning (ICSADL)*, IEEE Computer Society, Mar. 2024, pp. 642–646. doi: <https://doi.org/10.1109/ICSADL61749.2024.00110>
- [4] V. Sai Chitti Subrahmanyam *et al.*, "Smart warehouse management system," in *Recent Trends in Renewable Energy Sources and Power Conversion*, R. Seyezhai, S. Karuppuchamy, and L. Ashok Kumar, Eds., Singapore: Springer, 2021, pp. 99–114. doi: https://doi.org/10.1007/978-981-16-0669-4_8.
- [5] X. Wang, V. Kumar, A. Kumari, and E. Kuzmin, "Impact of digital technology on supply chain efficiency in manufacturing industry," in *Digital Transformation in Industry*, V. Kumar, J. Leng, V. Akberdina, and E. Kuzmin, Eds., Cham: Springer International Publishing, 2022, pp. 347–371. doi: https://doi.org/10.1007/978-3-030-94617-3_25.
- [6] S. Raharno and G. Cooper, "Jumping to Industry 4.0 through process design and managing information for smart manufacturing: Configurable virtual workstation," in *Industry 4.0 – Shaping The Future of The Digital World*, vol. 1, in 1, vol. 1, CRC Press, 2020, p. 5. <https://www.taylorfrancis.com/chapters/edit/10.1201/9780367823085-9/jumping-industry-4-0-process-design-managing-information-smart-manufacturing-configurable-virtual-workstation-raharno-cooper>
- [7] S. Raharno and V. S. Yosephine, "Intelligent flexible assembly system for labor-intensive factory using the configurable virtual workstation concept," *Int J Interact Des Manuf*, vol. 18, no. 1, pp. 465–478, Jan. 2024, doi: <https://doi.org/10.1007/s12008-023-01567-3>.
- [8] A. Tarallo, R. Mozzillo, G. Di Gironimo, and R. De Amicis, "A cyber-physical system for production monitoring of manual manufacturing processes," *Int J Interact Des Manuf*, vol. 12, no. 4, pp. 1235–1241, Nov. 2018, doi: <https://doi.org/10.1007/s12008-018-0493-5>.
- [9] V. Systems, "The Ultimate Guide to RFID Costs," Vertical systems inc. Accessed: Sep. 22, 2024. [Online]. Available: <https://vertsys.com/guide-to-rfid-costs/>
- [10] S. Teerasoponpong and A. Sopadang, "Decision support system for adaptive sourcing and inventory management in small- and medium-sized enterprises," *Robotics and Computer-Integrated Manufacturing*, vol. 73, p. 102226, Feb. 2022, doi: <https://doi.org/10.1016/j.rcim.2021.102226>.
- [11] S. Y. Tanjung, K. Yahya, and S. Halim, "Predicting the readiness of Indonesia manufacturing companies toward Industry 4.0: A machine learning approach," *Jurnal Teknik Industri: Jurnal Keilmuan dan Aplikasi Teknik Industri*, vol. 23, no. 1, Art. no. 1, May 2021, doi: <https://doi.org/10.9744/jti.23.1.1-10>.
- [12] R. P. Sari and D. T. Santoso, "Readiness factor identification on Kabupaten Karawang SMEs towards Industry 4.0 Era," *Jurnal Teknik Industri: Jurnal Keilmuan dan Aplikasi Teknik Industri*, vol. 22, no. 1, pp.65-74, 2020, doi: <https://doi.org/10.9744/jti.22.1.65-74>.
- [13] T.-C. Wen, Y.-C. Chang, and K.-H. Chang, "Cost-benefit analysis of RFID application in apparel retailing for SME: A case from Taiwan," *Transportation Journal*, vol. 49, no. 3, pp. 57–66, 2010. <https://www.jstor.org/stable/40904905>.
- [14] M. Hehua, "Application of passive Wireless RFID Asset Management in Warehousing of Cross-Border E-Commerce Enterprises - Hehua - 2021 - *Journal of Sensors* - Wiley Online Library." Accessed: Sep. 22, 2024. [Online]. Available: <https://onlinelibrary.wiley.com/doi/full/10.1155/2021/6438057>
- [15] L. Louw and M. Walker, "Design and implementation of a low cost RFID track and trace system in a learning factory," *Procedia Manufacturing*, vol. 23, pp. 255–260, Jan. 2018, doi: <https://doi.org/10.1016/j.promfg.2018.04.026>.
- [16] K. Sangsane and A. Vanichchinchai, "Improvement of warehouse storage area and system: An application of visual control and barcode," in *2021 IEEE 8th International Conference on Industrial Engineering and Applications (ICIEA)*, Apr. 2021, pp. 444–448. doi: <https://doi.org/10.1109/ICIEA52957.2021.9436727>.
- [17] M.-H. Lin, M. A. Sarwar, Y.-A. Daraghmi, and T.-U. İk, "On-shelf load cell calibration for positioning and weighing assisted by activity detection: Smart store scenario," *IEEE Sensors Journal*, vol. 22, no. 4, pp. 3455–3463, Feb. 2022, doi: <https://doi.org/10.1109/JSEN.2022.3140356>.

- [18] P. Octaviani and W. Ce, "Inventory placement mapping using Bluetooth low energy beacon technology for warehouses," in *2020 International Conference on Information Management and Technology (ICIMTech)*, Aug. 2020, pp. 354–359. doi: <https://doi.org/10.1109/ICIMTech50083.2020.9211206>.
- [19] F. Han *et al.*, "Improvement of monitoring production status of iron and steel factories based on thermal infrared remote sensing," *Sustainability*, vol. 15, no. 11, Art. no. 11, Jan. 2023, doi: <https://doi.org/10.3390/su15118575>.
- [20] M. Hehua, "Application of passive wireless RFID asset management in warehousing of cross-border e-commerce enterprises," *Journal of Sensors*, vol. 2021, no. 1, p. 6438057, 2021, doi: <https://doi.org/10.1155/2021/6438057>.
- [21] M. Batara and V. S. Yosephine, "Alat pendeteksi stok barang berbasis IoT untuk UMKM dengan sensor ultrasonik dan inframerah," *Journal of Integrated System*, vol. 7, no. 1, Art. no. 1, Jun. 2024, doi: <https://doi.org/10.28932/jis.v7i1.8525>.
- [22] B. Scholten, *The Road to Integration: A Guide to Applying the ISA-95 Standard in Manufacturing*. ISA, 2007. Available: <https://www.isa.org/products/the-road-to-integration-a-guide-to-applying-th-1>
- [23] A. Schumacher, T. Nemeth, and W. Sihn, "Roadmapping towards industrial digitalization based on an Industry 4.0 maturity model for manufacturing enterprises," *Procedia CIRP*, vol. 79, pp. 409–414, Jan. 2019, doi: <https://doi.org/10.1016/j.procir.2019.02.110>.

