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IoT-Based Real-Time Monitoring System for Post-Harvest Fish Storage Quality

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Abstract- This study develops an Internet of Things (IoT)-based system for continuously monitoring the environmental conditions and freshness indicators of post-harvest fish storage. The system integrates an ESP32 microcontroller with a DHT22 temperature-humidity sensor, an MQ-137 ammonia sensor, and an analog pH probe. Sensor measurements are sampled every five seconds, transmitted through Wi-Fi using the MQTT publish-subscribe protocol, stored in a MySQL database through a Node.js backend, and visualized on a React.js web dashboard. A research-and-development design with iterative prototyping was applied, followed by sensor calibration, integration testing, transmission-performance testing, and a 72-hour storage experiment using tuna and snapper samples. The system achieved average accuracies of 97.3% for temperature, 96.8% for relative humidity, 94.2% for ammonia, and 95.1% for pH. Average end-to-end latency was 0.856 s on a local network, 1.230 s on a 10 Mbps Internet connection, and 2.145 s on a 5 Mbps connection. Continuous operation for seven days produced 99.2% uptime. During the storage test, ammonia increased from below 2 ppm to 28.4 ppm while pH decreased from 6.8 to 5.2. The dashboard issued warning and critical alerts when predefined ammonia thresholds were exceeded, demonstrating its capability for timely quality-risk detection.

Keywords: Internet of Things; fish storage; post-harvest monitoring; ammonia sensor; MQTT

1. INTRODUCTION

Indonesia's fisheries sector has substantial economic and food-security importance. National capture-fisheries production reaches millions of tonnes annually and supports a broad network of fishers, traders, processors, cold-storage operators, and distributors [1]. Nevertheless, the value created at the harvesting stage is frequently reduced during post-harvest handling. The Food and Agriculture Organization reports that fish losses in developing supply chains can remain high when icing, storage, transportation, and quality supervision are inadequate [2]. Fish is particularly vulnerable because its high water activity, neutral initial pH, endogenous enzymes, and nutrient-rich tissue provide favorable conditions for biochemical deterioration and microbial growth. Consequently, a monitoring failure of only a few hours may cause a significant decline in sensory quality, food safety, and market value.

Temperature control is the primary intervention for slowing fish spoilage. Fresh fish stored close to 0-2 °C can maintain acceptable quality considerably longer than fish exposed to higher temperatures [3], [4]. Relative humidity also influences dehydration, surface condition, condensation, and microbial development inside a storage room. However, temperature and humidity alone cannot fully represent freshness deterioration. Spoilage bacteria and enzymatic degradation produce volatile nitrogen compounds, including ammonia and trimethylamine, while biochemical changes alter the pH of fish tissue and the surrounding measurement medium [5][6]. Ammonia concentration and pH are therefore useful electronic indicators that complement routine organoleptic inspection. Their continuous measurement can reveal a deterioration trend before the change is clearly recognized through appearance or odor.

Conventional monitoring in small and medium fish businesses is commonly performed through periodic manual observation. Operators inspect thermometers, smell the product, or open storage units to visually assess the fish. This approach creates long intervals without information, depends strongly on human availability, and provides little historical evidence for evaluating storage performance. Manual inspection also becomes inefficient when several rooms, containers, or distribution points must be supervised simultaneously. A practical monitoring platform should therefore acquire multiple parameters automatically, preserve time-stamped records, and immediately notify responsible personnel when the measurements leave a safe operating range.

The Internet of Things offers an appropriate technological framework for this requirement. IoT connects identifiable physical objects, sensors, communication networks, processing services, and user applications so that data can be collected and exchanged with limited direct intervention [7][8]. In food supply chains, connected sensing has been used to supervise temperature, traceability, preservation conditions [9], and logistics performance [10], [11]. Intelligent packaging and sensor-based freshness indicators further demonstrate that environmental and biochemical information can be translated into actionable quality signals [12]. These developments show that low-cost sensing, communication, and visualization can support continuous supervision where conventional laboratory instruments are not always available.

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Prior research has addressed complementary aspects of post-harvest quality. Cold-chain studies emphasize temperature management, monitoring, and time-temperature control [13], [14]. Sensor-oriented work covers intelligent packaging, electronic noses, and advanced aquatic-product freshness assessment [15], [16]. Nugroho et al. implemented IoT-based monitoring and active temperature stabilization for fish storage, but the system remained focused on thermal conditions [17]. These studies establish the value of connected sensing, yet they do not combine temperature, relative humidity, ammonia, and pH with historical visualization and staged alerts in one affordable platform.

The remaining research gap is integration. The platform must monitor four parameters, use lightweight communication, store time-stamped data, visualize current and historical trends, and issue configurable alerts. MQTT is suitable because its publish-subscribe model is lightweight for constrained machine-to-machine and IoT communication . The ESP32 is appropriate because it combines processing, sensor interfacing, and integrated Wi-Fi connectivity in a compact platform that has been implemented successfully in IoT monitoring applications [18], [19].

This study therefore develops and evaluates an IoT-based real-time monitoring system for post-harvest fish storage. The system consists of a multi-sensor acquisition node, MQTT communication, cloud-based data services, a relational database, and a responsive web dashboard. The research focuses on four objectives: designing the integrated architecture; implementing the ESP32, sensors, MQTT broker, backend, database, and dashboard; measuring sensor accuracy and system performance; and evaluating the ability of threshold-based alerts to identify deteriorating storage conditions. Unlike an active refrigeration controller, the proposed product is a monitoring and early-warning platform. Its intended contribution is a technically measurable and economically accessible foundation for improving post-harvest supervision in small and medium fisheries operations.

2. RESEARCH METHODOLOGY

2.1 Research Design and Development Workflow

The study used a research-and-development design with an iterative prototyping approach. This approach was selected because the output was a functional hardware-software product whose requirements, sensor behavior, communication process, and interface had to be refined through repeated testing. The research was organized into six connected stages: literature review and problem identification, requirement analysis, system design, implementation, testing and validation, and result interpretation. The literature stage examined post-harvest fish deterioration, sensor characteristics, IoT architecture, MQTT communication, and related monitoring applications. Requirement analysis translated the practical problem into functional requirements such as multi-parameter acquisition, real-time data transmission, historical storage, visualization, and alerts, as well as non-functional targets for accuracy, latency, uptime, and implementation cost. Figure 1 summarizes the complete workflow.

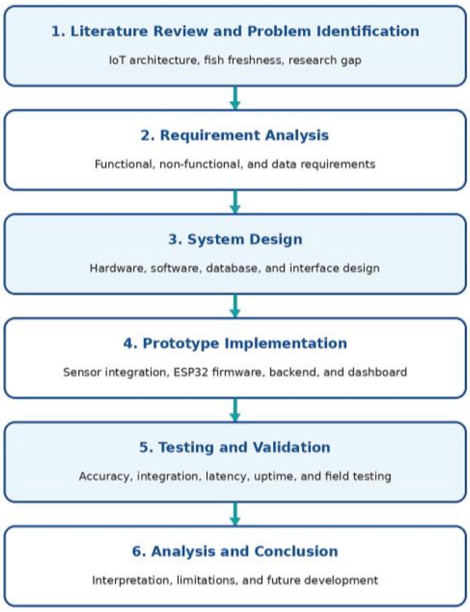

Figure 1. Research and development workflow

2.2 System Architecture and Data Flow

The architecture comprised four logical layers. The sensor layer contained a DHT22 for temperature and relative humidity, an MQ-137 for ammonia, and an analog pH probe. These devices were connected to an ESP32 development board that acquired measurements and performed initial validation. The gateway and communication layer used the ESP32 integrated Wi-Fi interface and an MQTT client. Measurements were published using hierarchical topics for temperature, humidity, ammonia, and pH. The cloud layer contained the Mosquitto MQTT broker, a Node.js/Express backend, and a MySQL database. The backend subscribed to sensor topics, validated message structure, stored records with timestamps, and exposed REST endpoints for historical queries. A WebSocket connection was used to push current data to the dashboard without waiting for repeated HTTP polling. The application layer was a responsive React.js interface that displayed current measurements, trends, recent records, device status, and alerts. Figure 2 illustrates the relationship among these layers.

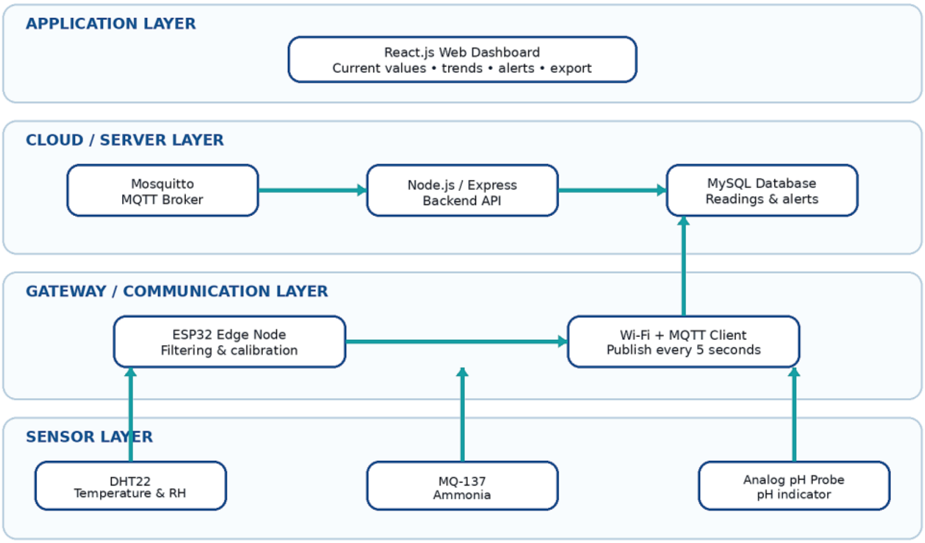

Figure 2. Layered IoT architecture for post-harvest fish-storage monitoring

2.3 Hardware and Software Implementation

The ESP32 was programmed using Arduino IDE. The DHT22 data pin was connected to GPIO4 with a 10 kΩ pull-up resistor. The MQ-137 analog output was connected to ADC pin GPIO34, while the pH conditioning-module output was connected to ADC pin GPIO35. A five-volt regulated supply powered the node, and the sensing circuit was assembled first on a breadboard and subsequently on a custom printed circuit board. The MQ-137 was preheated before calibration, and its analog response was converted to ammonia concentration using the calibration relationship derived from reference measurements. The pH probe was calibrated using pH 4.0 and pH 7.0 buffer solutions. Temperature and humidity readings were compared with calibrated digital instruments. Range checking was applied before publication to prevent physically implausible values from entering the database. The primary measurement interval was five seconds. If Wi-Fi or MQTT communication failed, the firmware attempted automatic reconnection and resumed publishing after connectivity returned.

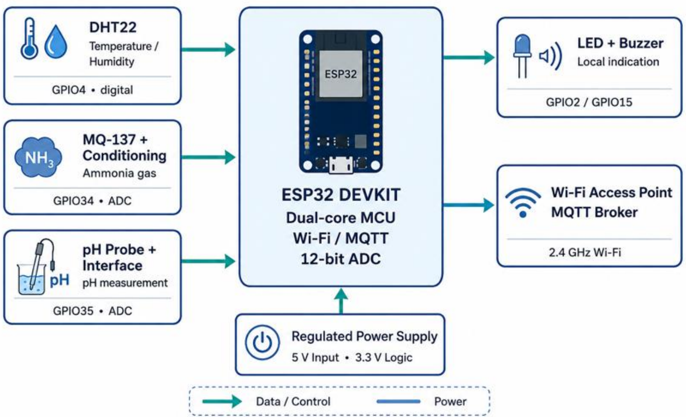

Figure 3. Hardware interconnection of the ESP32 and sensing modules

Table 1. Core hardware and software configuration

Component	Specification or technology	Primary function
ESP32 DevKit	Dual-core MCU, Wi-Fi, 12-bit ADC	Acquisition, preprocessing, and communication
DHT22	-40 to 80 °C; 0-100% RH	Temperature and relative humidity
MQ-137	Nominal detection range 5-500 ppm NH3	Ammonia-related freshness indicator
Analog pH probe	Measurement range 0-14 pH	Acidity indicator
Mosquitto / MQTT	QoS-based publish-subscribe messaging	Sensor-to-server transport
Node.js / Express	Backend service and REST API	Message processing and data access
MySQL 8.0	Relational database	Historical records and alerts
React.js / Chart.js	Responsive web application	Visualization and notification

To clarify the physical integration of the controller, sensing modules, probe interface, and protective enclosure, Figure 4 presents an illustrative visualization prepared from the documented prototype specification. The visualization shows the ESP32 node, DHT22, MQ-137, pH interface and probe, wiring, and enclosure arrangement used as the design reference.

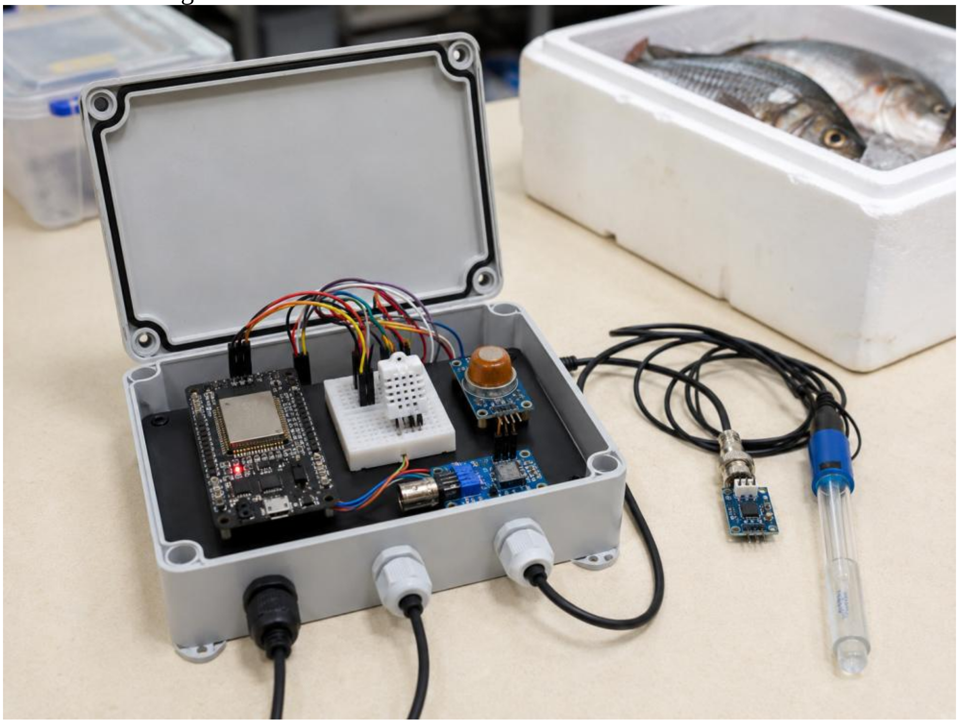

Figure 4. Illustrative visualization of the IoT prototype configuration

2.4 Database, Dashboard, and Alert Logic

The database contained four main entities: devices, sensor_readings, alerts, and users. Each sensor record stored the device identifier, temperature, relative humidity, ammonia, pH, and timestamp. Alert records referenced the triggering measurement and stored the parameter type, threshold, message, and resolution status. The dashboard presented four current-value indicators, a 24-hour trend chart, the latest records, device selection, date-range filtering, and data export. Threshold colors were green for normal, yellow for warning, and red for critical conditions. For the storage experiment, an ammonia value above 10 ppm generated a warning and a value above 25 ppm generated a critical alert. Notifications were shown on the dashboard and sent by email. The combined data-flow and database model is shown in Figure 5.

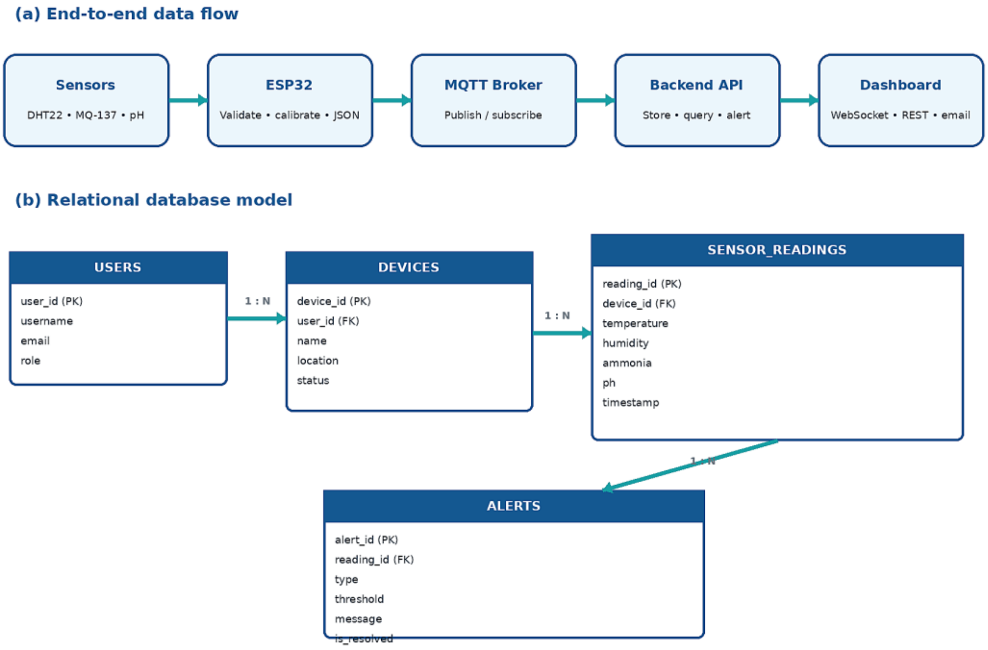

Figure 5. Data transmission flow and relational data model

2.5 Testing Procedure and Data Analysis

Testing was conducted at component, integration, communication, and field levels. Sensor accuracy was evaluated by comparing the prototype readings with calibrated reference instruments under controlled conditions. The references consisted of a digital thermometer with ±0.1 °C accuracy, a hygrometer with ±1% RH accuracy, a professional ammonia detector with ±2 ppm accuracy, and a laboratory-grade pH meter with ±0.01 pH accuracy. Measurements were repeated three times at each test point. Mean absolute error and percentage accuracy were calculated for every parameter, and linear agreement was examined using the coefficient of determination. End-to-end latency was defined as the interval between sensor acquisition and appearance on the dashboard. One hundred transmissions were tested under three network scenarios: local Wi-Fi, 10 Mbps Internet, and 5 Mbps Internet. Stability was evaluated through seven days of uninterrupted operation, during which disconnections, restarts, and downtime were logged.

Field testing was performed for 72 hours in a 3 m × 2 m × 2.5 m refrigerated storage room containing tuna and snapper samples. The cooling unit maintained a nominal temperature of 2-4 °C and relative humidity of 85-90%. Each parameter was sampled every five seconds, resulting in 51,840 records per sensor. The analysis emphasized the temporal relationship among storage conditions, ammonia increase, pH decrease, and generated alerts. The predefined non-functional targets were ±0.5 °C temperature error, ±5% RH humidity error, ±5 ppm ammonia error, ±0.2 pH error, latency below five seconds, and uptime above 95%. Descriptive statistics were used to summarize accuracy, latency, uptime, and changes across the 72-hour experiment.

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Figure 6 provides an illustrative visualization of the insulated fish-storage box and sensor placement based on the documented field-test configuration. The sensing probes are positioned to capture the storage environment and freshness-related indicators while the protected IoT node remains outside the ice and fish-contact area.

Figure 6. Illustrative visualization of the monitored fish-storage box and sensor placement

3. RESULT AND DISCUSSION

3.1 Sensor Calibration and Accuracy

The integrated sensor node successfully acquired all four parameters and transmitted a complete measurement payload at the configured five-second interval. Table 2 presents the comparison between each sensor and its reference instrument. The DHT22 produced a mean temperature error of ±0.34 °C over the 0-30 °C test range, corresponding to 97.3% accuracy. Relative-humidity error averaged ±2.1% RH over the 60-95% RH range, producing 96.8% accuracy. The MQ-137 produced a mean error of ±2.8 ppm within the 0-50 ppm evaluation range and achieved 94.2% accuracy. The analog pH system produced a mean error of ±0.15 pH units over pH 4-10 and achieved 95.1% accuracy. All errors remained inside the non-functional limits defined during system design.

Table 2. Sensor accuracy against calibrated reference instruments

Parameter	Test range	Mean error	Accuracy	R^2
Temperature	0-30 °C	±0.34 °C	97.3%	0.983
Relative humidity	60-95% RH	±2.1% RH	96.8%	0.976
Ammonia	0-50 ppm	±2.8 ppm	94.2%	0.951
pH	4-10	±0.15 pH	95.1%	0.962

The coefficients of determination ranged from 0.951 to 0.983, indicating strong linear agreement with the reference instruments. Temperature yielded the highest agreement because the DHT22 produces a factory-calibrated digital output and does not depend on analog conversion at the ESP32. Ammonia showed the lowest, although still acceptable, agreement. This result is consistent with the operating characteristics of metal-oxide gas sensors, which are influenced by warm-up stability, ambient humidity, sensor aging, and cross-sensitivity. The accuracy therefore reflects the calibrated experimental range rather than a claim that the MQ-137 is equivalent to a laboratory gas-analysis instrument. In practical deployment, periodic recalibration and stable heater operation remain necessary. The pH readings also met the target, but probe cleaning and two-point buffer calibration are essential because electrode drift can accumulate over time.

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The multi-sensor configuration provides more useful information than temperature-only monitoring. A stable temperature can indicate that the cooling equipment is operating, yet it cannot directly reveal whether the fish entered storage in a deteriorated condition or whether biochemical changes are already progressing. Ammonia and pH introduce complementary evidence of freshness change, consistent with ammonia-responsive indicators, intelligent sensing, and electronic-nose studies. Their combination with environmental temperature and humidity allows the dashboard to distinguish an infrastructure condition from a product-quality trend. This integration therefore extends systems that monitor only thermal conditions by adding freshness-related signals, networked records, and remote alerts.

3.2 Communication Latency and System Stability

The MQTT communication chain operated within the five-second real-time target in all network scenarios. Table 3 shows that local Wi-Fi produced a mean end-to-end latency of 856 ms. When the broker and application were accessed through a 10 Mbps Internet connection, mean latency increased to 1,230 ms. Reducing the connection to 5 Mbps increased mean latency to 2,145 ms, with a maximum of 4,780 ms. The increase was expected because the complete path included Wi-Fi transmission, broker processing, backend subscription, database insertion, WebSocket delivery, and browser rendering. Despite these stages, the worst observed maximum remained below the design threshold.

Table 3. End-to-end data-transmission latency

Network scenario	Minimum (ms)	Maximum (ms)	Mean (ms)	Target status
Local Wi-Fi	340	1,280	856	Met
Internet 10 Mbps	520	2,450	1,230	Met
Internet 5 Mbps	890	4,780	2,145	Met

The results support the selection of MQTT for this application. The protocol maintains a persistent connection and transmits compact messages through a broker, avoiding the repeated request overhead associated with frequent HTTP polling. For a storage-monitoring task, a delay of approximately one to two seconds is sufficiently short for operational awareness because quality changes occur over minutes or hours rather than milliseconds. More importantly, the automatic reconnection logic prevented temporary network interruptions from requiring manual device restart. The MQTT structure also permits future expansion: additional storage nodes can publish under different device identifiers while the same backend subscribes to the corresponding topic hierarchy.

During 168 hours of continuous operation, the system achieved 99.2% uptime. Total downtime was approximately 1.34 hours and was primarily associated with a 45-minute local power interruption and accumulated Wi-Fi reconnection periods of approximately 35 minutes. After an uninterruptible power supply was added, observed uptime increased to 99.7%. The initial result already exceeded the 95% requirement, but the failure log demonstrates that power continuity is as important as software reliability. A monitoring platform cannot issue alerts when its sensing node or router is unavailable. Therefore, production deployment should include backup power, network-health status, and a local buffering mechanism so that measurements acquired during a temporary outage can be uploaded after reconnection.

3.3 Seventy-Two-Hour Fish-Storage Monitoring

The 72-hour field experiment generated 51,840 time-stamped measurements for each parameter. The cooling unit generally maintained the environmental target of 2-4 °C and 85-90% RH, indicating that the principal observed quality change was not caused by a prolonged refrigeration failure. During the first hour, ammonia remained below 2 ppm and pH was approximately 6.8. After 24 hours, ammonia increased to an average of 5.3 ppm and pH decreased to 6.4. At 48 hours, average ammonia reached 12.7 ppm and pH decreased to 5.9. By 72 hours, average ammonia was 28.4 ppm and pH had fallen to 5.2. Table 4 summarizes these representative observations.

Table 4. Representative freshness-indicator trend during 72-hour storage

Storage time	Ammonia (ppm)	pH	System interpretation	Alert status
0-1 h	<2.0	≈6.8	Initial / fresh condition	Normal
24 h	5.3	6.4	Early quality change	Normal
48 h	12.7	5.9	Significant deterioration	Warning
72 h	28.4	5.2	Severe deterioration	Critical

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The ammonia trajectory is consistent with the accumulation of volatile nitrogen compounds during protein degradation and microbial activity. The pH decline observed in the test also indicates ongoing biochemical change within the fish sample measurement system. These two signals moved in the expected deterioration direction and provided a clearer temporal pattern than an isolated measurement. The warning threshold of 10 ppm was crossed at approximately hour 36, whereas the critical threshold of 25 ppm was crossed at approximately hour 62. Consequently, the system produced an early warning roughly 26 hours before the critical ammonia condition. This interval is operationally meaningful because it provides time for an operator to inspect the product, verify refrigeration, improve icing, separate affected batches, accelerate distribution, or perform a confirmatory quality test.

The observed pH values must be interpreted as an indicator from the calibrated probe and test medium rather than a complete substitute for standardized laboratory quality assessment. Fish freshness is multidimensional and is normally evaluated through sensory examination, volatile basic nitrogen compounds, microbial count, electronic sensing, and other validated methods. The proposed system is therefore intended for screening and early warning, not for issuing a regulatory food-safety certificate. Its value lies in continuous trend detection: when ammonia rises rapidly or pH changes beyond the normal pattern, the system identifies a batch that requires immediate attention. This interpretation prevents overstatement of the low-cost sensors while preserving their practical role in risk-based supervision.

3.4 Dashboard Visualization and Alert Response

The React.js dashboard successfully presented the latest temperature, humidity, ammonia, and pH values in a single view. Each indicator changed color according to its configured status, while a line chart showed the recent trend and a table listed time-stamped records. Device filters and date-range controls allowed the user to inspect current or historical measurements. Comparable dashboard-based visualization has been used to transform large operational datasets into interpretable patterns and decision-support [20]. Figure 7 shows the implemented interface. The dashboard received current values through WebSocket communication, so users did not need to refresh the page manually. Historical requests were handled through the REST API, which reduced unnecessary transmission of the complete database during routine real-time observation.

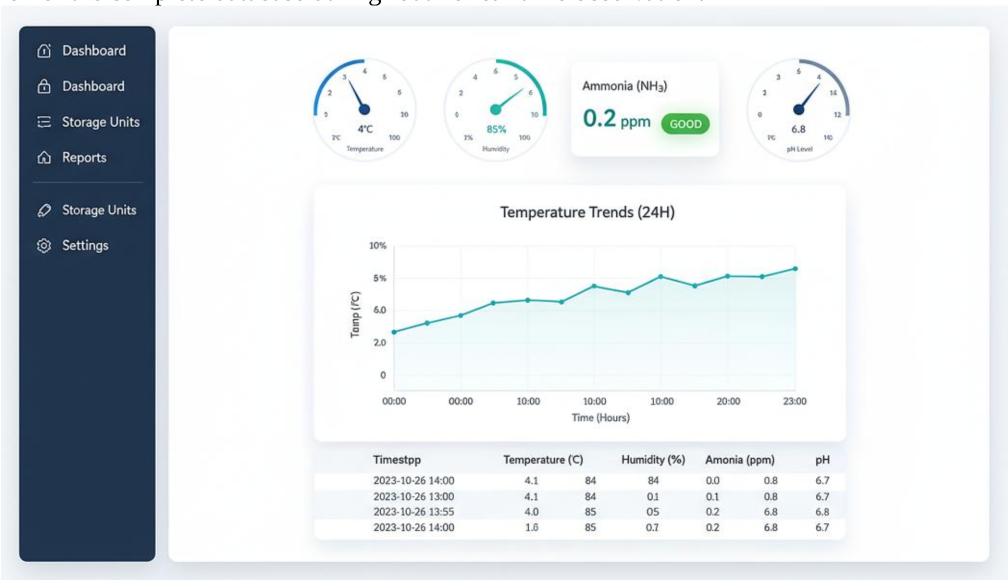

Figure 7. Web dashboard for current measurements, trends, and recent records

When the 10 ppm warning threshold was exceeded, the system generated a dashboard and email notification in less than three seconds. A second critical notification was produced after ammonia exceeded 25 ppm. The separation between warning and critical levels is preferable to a single binary alarm because it supports staged decision making. A warning invites verification and preventive action, whereas a critical alarm indicates that the risk has become urgent. The alerts were also stored in the database with their triggering readings, creating an auditable history that can be used to evaluate operator response and recurring storage problems.

3.5 Comparative Discussion, Cost, and Limitations

The developed platform combines capabilities that are usually separated across earlier studies. Smart cold-chain research has emphasized preservation, traceability, and logistics , whereas seafood-quality studies have focused on electronic noses and advanced freshness sensors. IoT-based fish-storage research has demonstrated remote temperature monitoring and active thermal stabilization, while a recent systematic review published in March 2025 confirms the growing use of IoT sensors for real-time monitoring of temperature, pH, ammonia-related parameters, and wireless data visualization in fisheries and aquaculture [21]. The present system extends these directions to post-harvest storage through a low-cost multi-sensor node that jointly observes the storage environment and freshness-related signals, uses MQTT for real-time cloud communication, and supplies current and historical web visualization. Its calibrated sensor accuracy and measured latency are adequate for trend-based operational monitoring.

The listed core hardware cost was approximately IDR 690,000, excluding optional backup power, server rental, installation accessories, and long-term maintenance. This cost level makes the prototype relevant to small and medium businesses, although affordability must be assessed against the number of rooms and required sensor replacement interval. The architecture is scalable because one cloud application can receive data from multiple nodes. A future multi-node version could compare rooms, identify recurrent cold-chain deviations, calculate device-level availability, and support end-to-end traceability, which is an established requirement in digital fishery supply chains [22]. An actuator layer could also be added to control ventilation or refrigeration, but such an extension would transform the present monitoring system into a closed-loop control system and would require additional safety testing.

Several limitations should be recognized. First, the field experiment lasted 72 hours and involved tuna and snapper in one refrigerated room; broader validation is required across species, storage methods, seasons, and handling conditions. Second, metal-oxide gas sensors are susceptible to cross-sensitivity and environmental drift, so the MQ-137 cannot independently identify all volatile compounds responsible for spoilage. Third, the pH measurement procedure should be standardized further for repeated commercial sampling and contamination control. Fourth, the study evaluated technical alert responsiveness but did not report a formal usability survey or a controlled comparison of operator efficiency. Finally, the system relied on Wi-Fi coverage. These limitations define the next research priorities: calibrated multi-gas sensing, longer experiments, standardized reference tests, user-centered evaluation, offline data buffering, LoRaWAN connectivity, and predictive shelf-life modeling. The illustrative visualizations in Figures 4 and 6 were prepared from the documented system specification to clarify the prototype and test arrangement; original experimental photographs should replace them before final journal submission when available.

4. CONCLUSION

An IoT-based real-time monitoring system for post-harvest fish storage was successfully developed by integrating an ESP32, DHT22, MQ-137, analog pH probe, MQTT broker, Node.js backend, MySQL database, and React.js dashboard. The prototype measured temperature, relative humidity, ammonia, and pH every five seconds and delivered the records to a cloud application. Calibration tests produced accuracies of 97.3% for temperature, 96.8% for humidity, 94.2% for ammonia, and 95.1% for pH. Average end-to-end latency ranged from 0.856 s on local Wi-Fi to 2.145 s on a 5 Mbps Internet connection, while seven-day uptime reached 99.2%. During the 72-hour storage experiment, ammonia increased from below 2 ppm to 28.4 ppm and pH decreased from approximately 6.8 to 5.2. The platform generated a warning after ammonia exceeded 10 ppm and a critical alert after it exceeded 25 ppm, thereby providing a measurable early-warning interval for corrective action. The system is best positioned as a continuous screening and decision-support tool rather than a replacement for standardized laboratory freshness testing. Future development should extend species and storage validation, standardize pH sampling, improve gas selectivity and calibration, add offline buffering and alternative communication, evaluate usability with actual operators, and develop predictive shelf-life models from larger historical datasets.

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