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AI ENABLED IOT-BASED SMART FOOD GRAIN WAREHOUSE MONITORING AND PREDICTIVE PROTECTION SYSTEM USING MACHINE LEARNING

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Abstract : Food grain storage is essential for maintaining food quality and reducing post-harvest losses. This paper presents an AI-Enabled IoT-Based Smart Food Grain Warehouse Monitoring and Predictive Protection System for continuous and intelligent warehouse monitoring. The system uses an ESP32 microcontroller with a DHT11 temperature–humidity sensor, an MQ-135 air-quality sensor, a grain-moisture sensor, an LDR, a flame sensor, a magnetic door sensor and an IR sensor to monitor temperature, humidity, grain moisture, air quality, fire, door status, movement and light conditions. The collected data are transmitted over Wi-Fi to the ThingSpeak cloud platform for real-time logging and visualization. A Random Forest machine-learning model predicts grain spoilage risk, fungal growth risk, storage condition and Remaining Storage Life (RSL), while a Decision Tree-based AI model classifies the overall warehouse condition as Normal, Warning or Critical and generates preventive recommendations. A Warehouse Health Score (WHS), Smart Grain Health Index (SGHI) and Fungal Growth Risk Index (FGRI) are computed and displayed on a Streamlit dashboard with Plotly graphs. Based on the detected condition the system automatically operates an exhaust fan and water pump and raises buzzer/GSM alerts. The system was validated with data collected from an actual warehouse; the latest observation (30 °C, 55% RH, 157 ppm MQ-135) produced a WHS of 86.5/100 and a Normal classification that agreed with the field observation, giving 100% agreement over the available field observations. The proposed system thus integrates IoT, cloud computing, Random Forest ML and Decision Tree AI into a single predictive, user-friendly solution for improving food-grain warehouse safety and minimizing manual monitoring.

IndexTerms - Internet of Things (IoT), ESP32, ThingSpeak, Random Forest, Decision Tree, Food Grain Warehouse, Predictive Protection, Warehouse Health Score, Remaining Storage Life.

I. INTRODUCTION

Food grain storage is an important part of the agricultural supply chain because it helps maintain food availability throughout the year. After harvesting, grains are stored in warehouses for several months before distribution and consumption. During this storage period, grains can be affected by temperature, humidity, moisture, poor air quality, fire, insects, rodents and unauthorized access. If these conditions are not properly monitored, they can reduce grain quality and cause significant post-harvest losses.

Traditional food grain warehouses generally depend on manual inspection to identify changes in storage conditions. Manual monitoring is time-consuming and may not detect abnormal conditions at an early stage. In addition, continuous observation of temperature, humidity, moisture, air quality, fire hazards and movement is difficult for warehouse personnel. Therefore, an automated system capable of continuously monitoring and analyzing warehouse conditions is required.

The proposed system provides an intelligent solution for real-time warehouse monitoring. An ESP32 controller is used as the main processing unit to collect data from multiple sensors. A DHT11 sensor monitors temperature and humidity, while an MQ-135 sensor monitors air quality. A moisture sensor measures the moisture condition of the stored grains, helping to identify conditions that may lead to spoilage or fungal growth. An LDR sensor is incorporated for abnormal light detection, a flame sensor detects fire, a magnetic door sensor detects unauthorized opening of the warehouse door and an IR sensor detects movement that may indicate pest or rodent activity. Based on the monitored conditions, an exhaust fan can be activated to improve ventilation and a water pump can be controlled as part of the protection mechanism.

The collected sensor data are transmitted through the ThingSpeak IoT platform for real-time monitoring, visualization, data storage and alert generation. A Random Forest machine-learning algorithm analyses multiple environmental parameters to predict the risk of grain spoilage and abnormal storage conditions, and a Decision Tree-based AI algorithm classifies the warehouse condition into Normal, Warning and Critical levels. The integration of IoT, machine learning and AI-based decision-making enables continuous monitoring and predictive protection of stored grains, providing early warnings and automatic preventive actions before serious damage occurs.

1.1 Objectives

- To develop an IoT-based smart food grain warehouse monitoring system using ESP32 for continuous monitoring of temperature, humidity, grain moisture, air quality, fire, door status and movement.
- To implement a Random Forest machine-learning model for grain spoilage detection, fungal growth risk prediction and Remaining Storage Life estimation.
- To calculate a Warehouse Health Score by combining multiple monitored parameters and evaluating the overall storage condition.
- To implement a Decision Tree-based AI model for classifying the warehouse condition into Normal, Warning and Critical levels and generating preventive recommendations.
- To automatically control the exhaust fan and water pump and to provide real-time cloud monitoring, alerts and data visualization for remote warehouse management.
- To validate the system using real-time data collected from an actual warehouse and thereby reduce grain spoilage and post-harvest losses.

II. LITERATURE SURVEY

Priyadarsani, Pradhan and Jena [1] reviewed the application of IoT technologies in food grain storage and highlighted the importance of real-time monitoring of temperature, humidity and other storage parameters. IoT can provide early warnings, environmental control, inventory monitoring and predictive analytics, and the review shows that IoT-based monitoring can reduce storage losses and improve food safety. Lutz et al. [2] developed a real-time equilibrium-moisture-content monitoring approach for corn stored in silos and raffia bags using wireless sensors, IoT and neural-network algorithms, demonstrating that real-time moisture monitoring can predict changes in grain quality. Artificial Neural Networks have also been used to predict fungal infestation in stored barley ecosystems [3], showing that environmental conditions can serve as inputs for predictive modelling of fungal growth.

Suganda et al. [4] developed an IoT-based grain storage monitoring system using DHT22 and MQ-135 sensors to identify possible spoilage and fungal-growth conditions, demonstrating the usefulness of continuous sensing over periodic manual inspection. Pratama, Nurchim and Bondan [5] built a smart rice-storage prototype in which an ESP32 was integrated with DHT22, LDR and moisture sensors, which is closely related to the hardware architecture of the proposed work. Latha [6] proposed an IoT-enabled grain storage monitoring framework for predictive spoilage detection and pest control, while Jain et al. [7] proposed AgriPulse, a smart grain storage system that warns when temperature, humidity or gas levels become abnormal. Bhandari et al. [8] combined IoT environmental monitoring with CNN-based grain-image analysis and used ThingSpeak for cloud-based visualization.

Several works on cold-chain and perishable-goods monitoring are also relevant. Rashid and Vasan [9] developed an IoT-based cold chain monitoring system generating alerts when parameters exceed predefined limits; Zhang and Chen [10] proposed a smart logistics framework using IoT sensors; Bhattacharya and Roy [11] proposed cloud-connected real-time monitoring of perishable goods; Patil and Kulkarni [12] investigated IoT-based fruit storage and transportation monitoring; Chen, Zhang and Li [13] studied multi-parameter IoT sensing for perishable goods; Li and Wang [14] examined GSM-based alert mechanisms for cold-chain logistics; and Patil and Suryawanshi [15] proposed a real-time environmental monitoring system for perishable goods using IoT. Gubbi et al. [16] and Al-Fuqaha et al. [17] provide the fundamental IoT architecture, enabling technologies and protocols on which the proposed system is built.

On the machine-learning side, Chen and Liu [18] evaluated Decision Tree, Extra Trees, AdaBoost and Random Forest models for temperature prediction in stored grain using a multi-model fusion approach and showed that ML models improve prediction accuracy and robustness, which strongly supports the use of Random Forest and Decision Tree algorithms in intelligent grain monitoring. Suhas G. K. [19] proposed a smart quality-monitoring framework for food grain storage using IoT and emphasized that significant losses occur because of inadequate monitoring, while Chen, Nowocin and Marathe [20] demonstrated a combined low-cost hardware and machine-learning software solution for reducing crop spoilage in India.

III. RESEARCH GAP

From the review of existing literature, it is observed that most studies on smart food-grain warehouses primarily focus on real-time monitoring of temperature, relative humidity, grain moisture and air quality using IoT-based systems. Several researchers have integrated cloud platforms for remote visualization, and some have employed machine learning for predicting grain quality and spoilage. However, these approaches are generally limited to monitoring or individual prediction tasks and provide comparatively little integration of multi-parameter sensing, predictive analysis, intelligent decision-making and automated preventive control within a single platform.

A significant gap exists in the combined use of environmental, grain-quality, air-quality, fire, security, light and movement parameters for comprehensive warehouse assessment. Existing systems also provide limited integration of Random Forest-based prediction and Decision Tree-based decision support for converting sensor data into understandable warehouse-condition classifications and preventive recommendations. Furthermore, indicators such as Warehouse Health Score (WHS), Smart Grain Health Index (SGHI), Fungal Growth Risk Index (FGRI), Pest Risk/Severity and Remaining Storage Life (RSL) are not commonly integrated into a single real-time monitoring framework; most conventional systems depend on threshold-based alerts that may not represent the combined influence of multiple conditions on grain quality.

Another important gap is the limited connection between prediction and automated preventive action, and the fact that many existing approaches are evaluated using datasets, simulations or controlled laboratory conditions with limited validation on actual warehouse data. The proposed work addresses these gaps by developing an integrated system using ESP32, multi-parameter sensors, ThingSpeak cloud, Random Forest ML, Decision Tree-based AI decision support, Streamlit and Plotly, combining real-time monitoring, cloud logging, predictive risk assessment, warehouse health scoring, RSL estimation, intelligent recommendations and preventive control in a unified platform validated with real warehouse data.

IV. PROPOSED SYSTEM

4.1 Existing System

In the existing food grain storage system, warehouse conditions are mainly monitored through manual inspection and basic measuring instruments. Temperature, humidity, moisture and grain quality are checked periodically by workers, and fire, pest activity or unauthorized access may be identified only after physical inspection. These methods do not provide continuous real-time monitoring or automatic alerts, and they have limited capability to analyse historical data and predict future spoilage, fungal growth risk, remaining storage life or overall warehouse health. As a result, problems may be detected only after significant damage has occurred.

4.2 System Architecture

The proposed system architecture is shown in Fig. 1. An ESP32 continuously collects data from the DHT11, MQ-135, grain-moisture, LDR, flame, magnetic door and IR sensors. The ESP32 drives an LCD display, buzzer, GSM module and a relay module that switches the cooling/exhaust fan and DC pump, and uploads the readings to the ThingSpeak cloud database. A camera module is provided for visual monitoring. The Random Forest model performs grain spoilage detection, fungal growth risk prediction and Remaining Storage Life estimation; a Warehouse Health Score is generated by combining the important storage parameters; and the Decision Tree AI model classifies the warehouse condition as Normal, Warning or Critical and recommends preventive actions, which the ESP32 executes automatically.

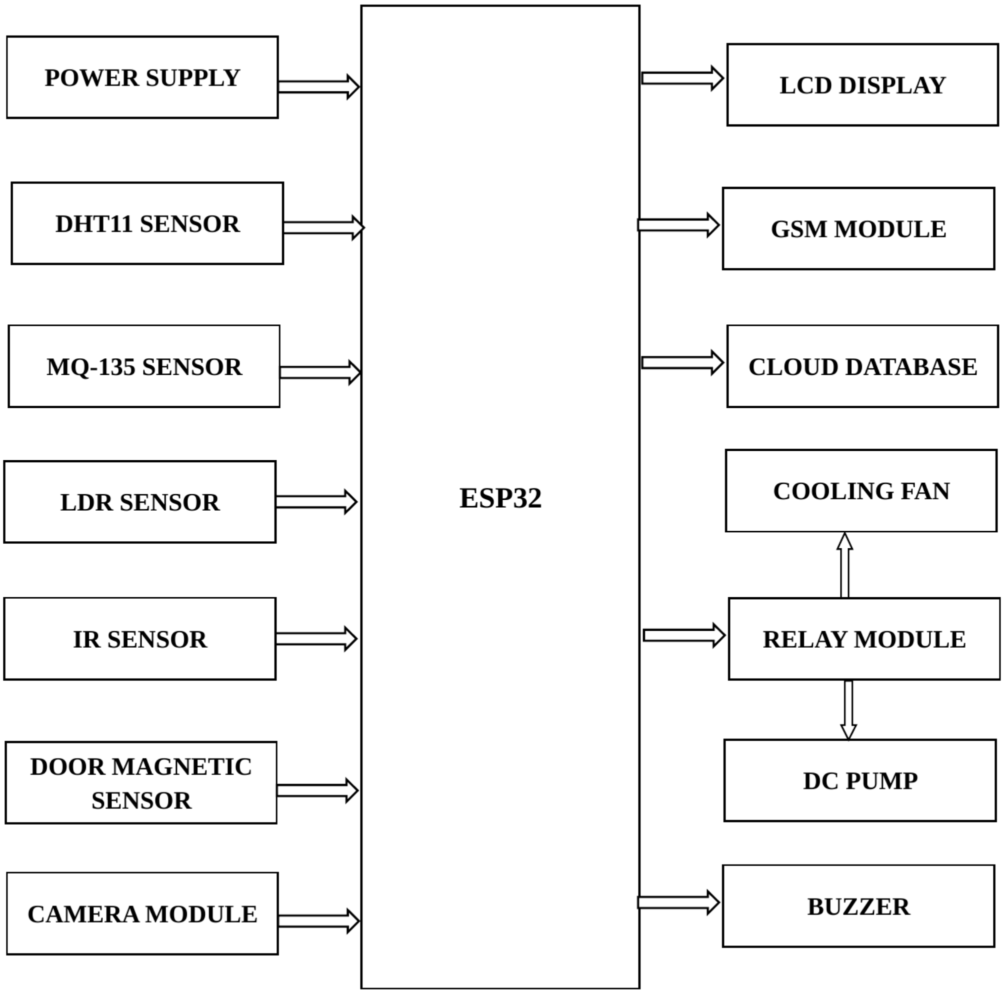

Fig. 1 Block diagram of the proposed system

The circuit diagram of the hardware is shown in Fig. 2. The DHT11 is connected to GPIO 25, the MQ-135 analog output to GPIO 34 and the moisture sensor to GPIO 35 of the ESP32; the flame, IR, LDR and door sensors are connected to digital inputs (GPIO 4, 26, 2 and 17), while the buzzer, fan relay and pump relay are driven from GPIO 23, 27 and 14. A 16×2 I2C LCD displays the readings locally.

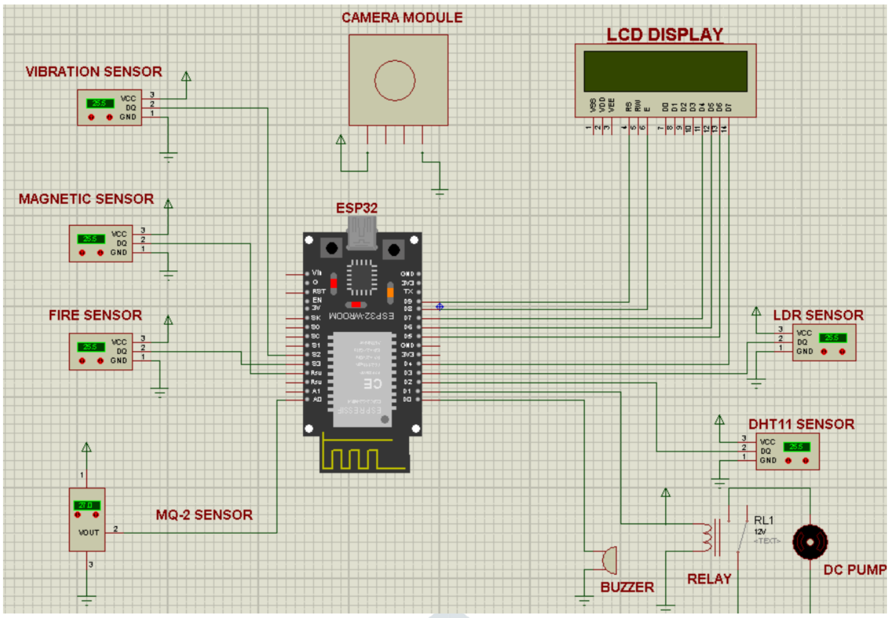

Fig. 2 Circuit diagram of the ESP32-based monitoring hardware

4.3 Hardware and Software Components

The hardware consists of an ESP32 (Wi-Fi + Bluetooth SoC, 4 MB PSRAM, 12-bit ADC), a 12 V/5 V regulated power supply, DHT11 temperature–humidity sensor (0–50 °C, 20–90% RH, ±1 °C/±1% accuracy), MQ-135 gas sensor (NH3, NOx, alcohol, benzene, smoke and CO2 detection, 5 V), resistive grain-moisture sensor with analog output, LDR light sensor, LM393-based flame sensor (3.3–5 V, 60° detection range), IR obstacle sensor with LM358 comparator, magnetic door sensor, 16×2 LCD, relay module, DC pump, cooling fan, camera module, SIM800L GSM module and a 5 V active buzzer (85 dB). Table 1 summarizes the component set.

Table 1: Hardware and software components of the proposed system

Category	Components / Tools	Function
Controller	ESP32 (ESP32-S / ESP32-CAM)	Data acquisition, control and Wi-Fi communication
Environmental sensors	DHT11, MQ-135, Grain moisture sensor	Temperature, humidity, air quality and grain moisture
Safety / security sensors	Flame sensor, LDR, IR sensor, Magnetic door sensor	Fire, abnormal light, movement/pest and door status
Actuators & alerts	Relay module, Exhaust/cooling fan, DC pump, Buzzer, GSM module, LCD	Preventive control, local display and SMS alerts
Cloud & software	ThingSpeak, Arduino IDE (Embedded C), Python, scikit-learn, Streamlit, Plotly	Data logging, firmware, ML models and dashboard

4.4 Working Principle

The ESP32 acts as the central control unit and collects real-time data from the sensors. The DHT11 measures temperature and humidity, the moisture sensor measures grain moisture and the MQ-135 monitors air quality. The flame sensor and LDR detect fire or abnormal light, the magnetic door sensor detects unauthorized door opening and the IR sensor detects movement or possible pest and rodent activity. The readings are displayed on the LCD and transmitted through Wi-Fi to ThingSpeak, where eight channel fields (temperature, humidity, gas, moisture, fire, IR, door and LDR events) are logged for real-time visualization and later analysis.

The firmware also implements threshold-based protection at the edge: the exhaust fan is switched on when the MQ-135 reading exceeds 2500 or the temperature exceeds 35 °C; abnormal light, movement or door opening triggers the buzzer and an LCD notification; and fire detection switches on the pump and buzzer and sends an SMS alert through the GSM module using AT commands. The temperature, humidity, moisture and air-quality data are then analysed by the Random Forest model for spoilage detection, fungal growth risk prediction and Remaining Storage Life estimation, the Warehouse Health Score is computed, and the Decision Tree model classifies the overall condition and identifies the appropriate preventive action, which is executed automatically by the ESP32.

V. AI AND MACHINE LEARNING METHODOLOGY

5.1 Random Forest Algorithm – Predictive Analysis

Random Forest is an ensemble machine-learning algorithm that combines multiple Decision Trees to produce a more reliable prediction. In the proposed system the temperature, humidity, grain moisture, air quality and warehouse environmental conditions are given as inputs, and the model outputs the Grain Spoilage Risk, Fungal Growth Risk, Remaining Storage Life and Storage Condition. The model is trained using historical sensor data containing different warehouse conditions and corresponding outcomes; during operation the real-time values from the ESP32 are provided to the trained model, multiple trees analyse the input and the final prediction is obtained by combining the results of all trees. For example, Temperature = 32 °C, Humidity = 80% and Grain Moisture = 16% results in Spoilage Risk = HIGH and Fungal Growth Risk = HIGH. The advantage of Random Forest is that it analyses multiple parameters together and generally provides more robust predictions than a single Decision Tree.

5.2 Decision Tree Algorithm – AI-Based Decision Support

A Decision Tree is used to make an intelligent decision based on the predicted results and current warehouse conditions through a series of if–then rules. For example, if humidity exceeds the safe limit and grain moisture exceeds the safe limit, the fungal growth risk is HIGH, the warehouse condition is set to WARNING and the exhaust fan is activated; if fire is detected, the condition is set to CRITICAL and an emergency alert is generated. The Decision Tree therefore converts the sensor and prediction results into simple and understandable actions, as summarized in Table 2.

Table 2: AI-based decision support rules

Condition	AI Decision	Action
Normal temperature & moisture	Normal	Continue monitoring
High humidity	Warning	Activate exhaust fan
High grain moisture	Warning	Generate alert
High fungal risk	Warning / Critical	Preventive action
High spoilage risk	Critical	Alert operator
Fire detected	Critical	Emergency alert, pump ON
Door opened unexpectedly	Warning	Security alert
Abnormal movement	Warning	Inspect warehouse

5.3 Predictive Indices

Grain Spoilage Detection: performed by analysing temperature, humidity, grain moisture and air quality; the Random Forest model learns patterns from historical storage data and classifies the spoilage risk as Low, Medium or High.

Fungal Growth Risk Prediction: fungal growth is mainly associated with unsuitable combinations of high humidity, high grain moisture and temperature. The model predicts the fungal growth probability as Low, Medium or High risk, and when the risk is high the Decision Tree recommends ventilation or other preventive action.

Remaining Storage Life (RSL) Estimation: historical and real-time storage parameters are used to estimate how long the grains can remain in safe storage, e.g. “Remaining Storage Life = 120 Days” or “65 Days – High Risk”. Continuous exposure to unsuitable temperature, humidity and moisture reduces the expected storage life. In the present prototype this is implemented as a prediction/classification model based on labelled historical data rather than an exact physical shelf-life measurement.

Warehouse Health Score (WHS): a 0–100 score calculated from temperature, humidity, moisture, air quality, fire status, security and movement, where 80–100 is Healthy, 60–79 Good/Monitor, 40–59 Warning and 0–39 Critical. The dashboard additionally reports the Smart Grain Health Index (SGHI), Fungal Growth Risk Index (FGRI) and Pest Risk/Severity (PRS).

VI. RESULTS AND DISCUSSION

6.1 Real-Time Cloud Monitoring

The prototype was deployed and evaluated in a real food grain warehouse. Fig. 3 shows the ThingSpeak channel graphs for temperature and relative humidity over the observation period; similar channels were logged for CO2/air quality, grain moisture, fire status, light intensity, door security and movement detection. The results demonstrate that the system can effectively perform continuous environmental monitoring, cloud-based data logging and security monitoring.

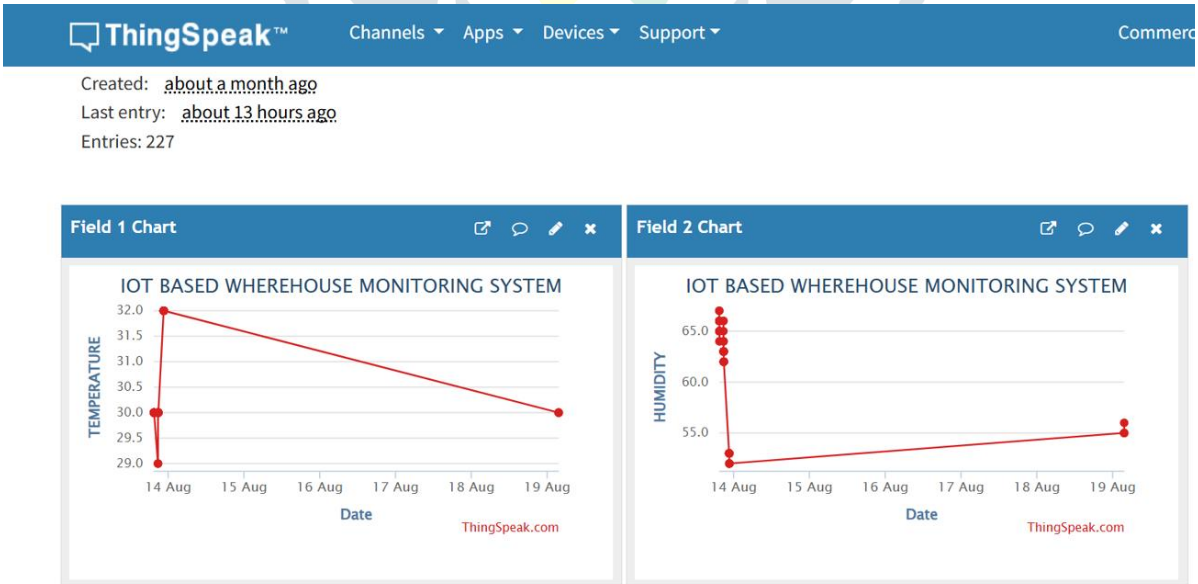

Fig. 3 ThingSpeak dashboard showing temperature and relative humidity monitoring

Fig. 4 shows the Streamlit-based real-time hardware telemetry dashboard synchronized with the ThingSpeak channel, and Fig. 5 shows the AI predictive indices generated from the same data. For the latest transmission (19 August 2026) the dashboard reported a temperature of 30.0 °C, relative humidity of 55.0%, MQ-135 reading of 157 ppm, grain moisture of 0.0%, fire state Clear, 0 insect events, door Secured and 0 light exposures.

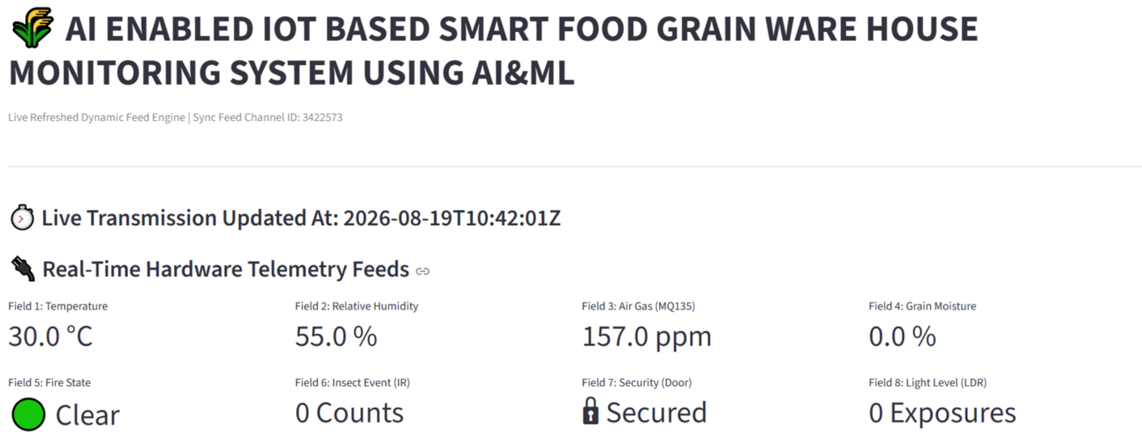

Fig. 4 Real-time hardware telemetry dashboard of the smart grain warehouse

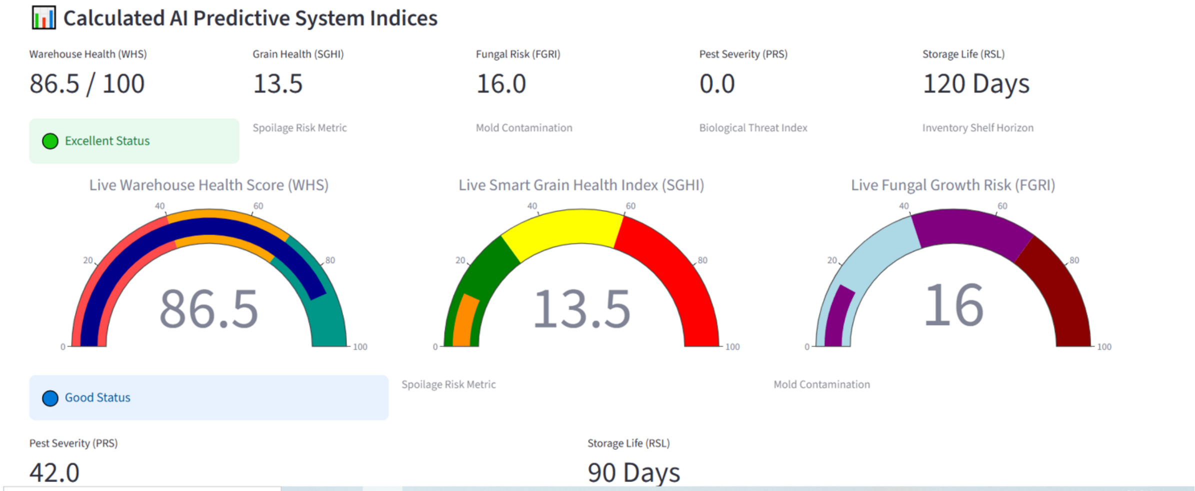

Fig. 5 AI predictive indices for warehouse and grain health assessment

6.2 Observations with Inferences

Table 3 summarizes the observed values from the real warehouse and the corresponding inferences. During the observed period no immediate fire, insect, security or excessive-light event was detected. The grain moisture reading of 0.0% must be validated through calibration, because an exactly zero value may indicate sensor scaling, wiring or calibration issues rather than actual grain moisture; low-cost resistive moisture sensors should be calibrated against a standard reference method for the particular grain being monitored.

Table 3: Observed warehouse parameters and inferences

Parameter	Sensor / Field	Observed Value	Observation	Inference
Temperature	DHT11	30.0 °C	Moderate temperature	Suitable warehouse condition; continuous monitoring required
Relative Humidity	DHT11	55.0 %	Moderate humidity	Fungal growth risk is comparatively low
Air quality / Gas	MQ-135	157 ppm	Gas concentration detected	Continuous air-quality monitoring needed
Grain Moisture	Moisture sensor	0.0 %	Very low / zero reading	Requires sensor calibration before use as a valid value
Fire	Flame sensor	0 / Clear	No fire detected	No immediate fire threat
Insect event	IR sensor	0 counts	No movement detected	No pest/insect activity during observation
Door	Magnetic sensor	Secured	Door closed	No unauthorized door opening
Light	LDR	0 exposures	No significant light	Warehouse remains dark/closed, desirable for stored grain

6.3 Comparison of Field Measurements

Two field observations were recorded, on 11 August 2026 and 19 August 2026. Table 4 and Fig. 6 compare the two measurements. The humidity decreased from 65% to 55%, the MQ-135 reading dropped from 1094 ppm to 157 ppm and the grain-moisture reading changed from 100% to 0%, while the fire, insect, door and light channels showed no change. The large changes in the MQ-135 and moisture channels indicate that the earlier measurement represented a Warning condition, whereas the later measurement represented a Normal condition.

Table 4: Field measurement comparison (11 Aug 2026 vs 19 Aug 2026)

Parameter	11 Aug 2026	19 Aug 2026	Change
Temperature	29 °C	30 °C	+1 °C
Humidity	65 %	55 %	−10 %
MQ-135	1094 ppm	157 ppm	−937 ppm
Grain moisture	100 %	0 %	−100 percentage points
Fire	Clear	Clear	No change
Insect movement	0	0	No change
Door	Secured	Secured	No change
Light	0	0	No change

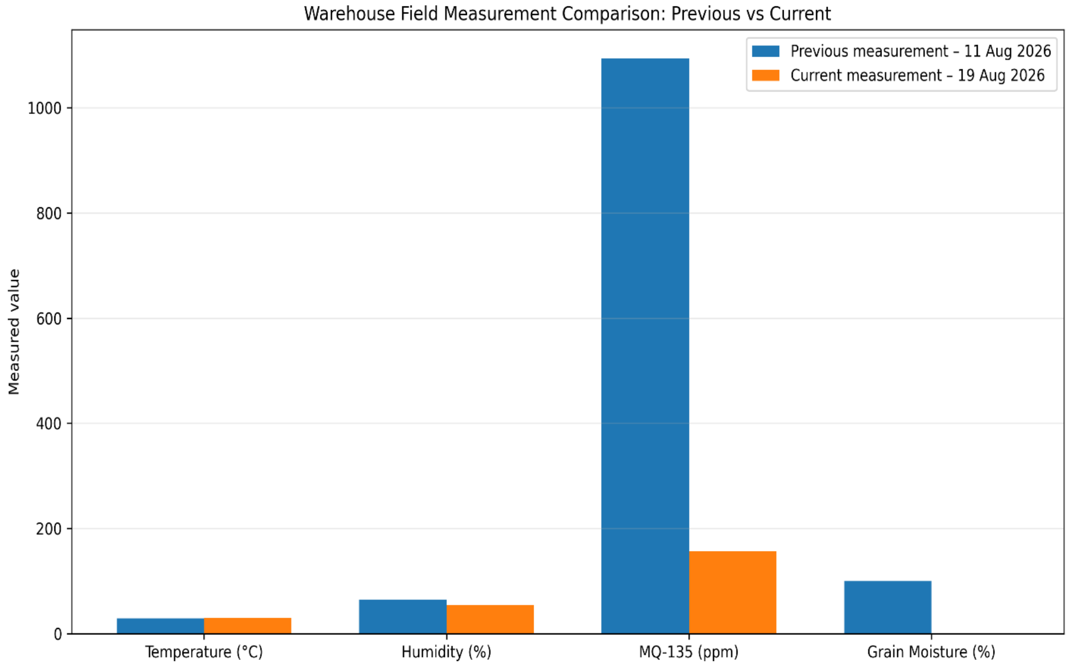

Fig. 6 Warehouse field measurement comparison: previous vs current observation

6.4 Predicted vs Actual Warehouse Condition

The Decision Tree model was evaluated by comparing its predicted condition with the actual warehouse condition for each observation. For the latest observation the AI-generated Warehouse Health Score was 86.5/100, the Smart Grain Health Index was 13.5, the Fungal Growth Risk Index was 16.0 and the estimated storage life was 120 days, indicating a healthy warehouse with low spoilage and fungal-growth risk. The AI-predicted condition was Normal/Healthy, and the field observation also indicated Normal/Healthy since no fire, insect event, unauthorized door opening or light exposure was observed (Fig. 7).

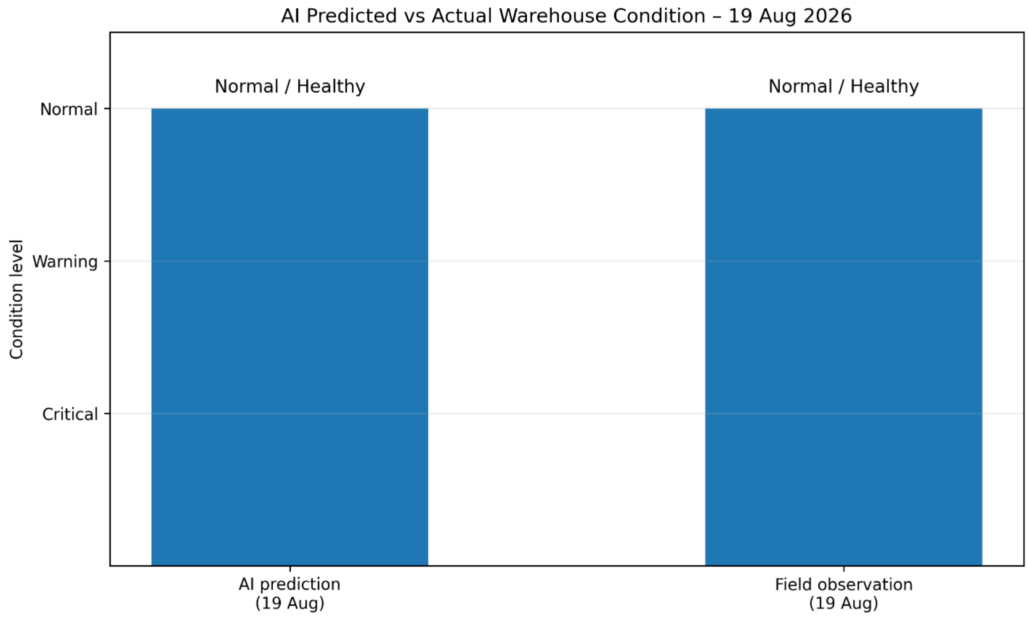

Fig. 7 AI predicted vs actual warehouse condition – 19 August 2026

Based on the measured parameters, the observation on 11 August 2026 was classified as Warning and the observation on 19 August 2026 as Normal, and the Decision Tree classification agreed with the observed warehouse condition in both cases, as shown in Table 5. Thus the Decision Tree showed 100% classification agreement for the two available field observations. It is noted that this agreement is based on a small number of field samples; a larger dataset is required for a statistically rigorous accuracy assessment.

Table 5: Decision Tree classification agreement with field observations

Date	Actual Warehouse Condition	Decision Tree Prediction	Result
11-08-2026	Warning	Warning	Correct
19-08-2026	Normal	Normal	Correct
Total	**2 observations**	**2 correct**	**100% agreement**

6.5 Role of IoT, AI and ML in the Proposed System

IoT is responsible for real-time data collection, communication, cloud storage, visualization and monitoring, acting as the connecting layer between the physical warehouse and the AI/ML system. Machine learning (Random Forest) provides the predictive analysis of spoilage risk, fungal growth risk and Remaining Storage Life from historical and real-time data, while AI (Decision Tree) converts the sensor data and ML outputs into Normal/Warning/Critical classifications, a Warehouse Health Score and recommended preventive actions. Together they change the system from a simple monitoring system into a predictive, intelligent decision-support and protection system.

VII. CONCLUSION AND FUTURE SCOPE

The proposed AI-Enabled IoT-Based Smart Food Grain Warehouse Monitoring and Predictive Protection System was successfully implemented and evaluated under real warehouse conditions. The ESP32-based system continuously acquired environmental, grain, air-quality, fire, security and movement parameters and transmitted them to the ThingSpeak cloud for real-time monitoring and visualization. For the observed data the system recorded 30.0 °C, 55.0% RH, an MQ-135 value of 157 ppm, a clear fire state, a secured door and no movement or light events, and the AI/ML module generated a Warehouse Health Score of 86.5/100, an SGHI of 13.5 and an FGRI of 16.0, indicating low spoilage and fungal-growth risk. The Decision Tree classification agreed with the field observations, and the integration of actual sensor observations with the AI-based predictive indices provides a more comprehensive assessment of warehouse health than monitoring individual parameters alone. The results confirm that the system is capable of real-time sensing, cloud-based monitoring, AI-assisted risk assessment, warehouse health evaluation and predictive protection for smart food grain warehouse management.

Future work can include deep-learning models (CNN, LSTM) for more advanced prediction of grain quality; computer vision using the camera module to detect mould, insects, rodents and damaged grains; a larger historical dataset to improve Remaining Storage Life estimation; a digital twin of the warehouse; automated climate control with ventilation, cooling and humidity regulation; advanced SMS, mobile-app and cloud notifications; centralized multi-warehouse monitoring; deployment of the ML model on the ESP32 or an edge device for faster local decisions; predictive maintenance of fans, pumps and electrical equipment; and validation with large-scale warehouse datasets for different grains such as rice, wheat, maize, pulses and millets.

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