

SILOSENSE: AN IOT-BASED CORN GRAIN SILO LEVEL MONITORING SYSTEM USING HC-SR04

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Keywords:

SiloSense;
Corn Grain Silo;
Level Monitoring;
HC-SR04;
Internet of Things.

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Abstrak. Ketersediaan biji jagung dalam silo produksi penting untuk menjaga keberlanjutan produksi tepung jagung. Namun, pemeriksaan level secara manual bersifat tidak kontinu, membutuhkan operator, dan rentan terhadap kesalahan pembacaan. Penelitian ini menyajikan SiloSense, prototipe sistem monitoring level silo biji jagung berbasis Internet of Things (IoT) menggunakan sensor ultrasonik HC-SR04, ESP8266 WeMos D1 Mini, display OLED SSD1306, Firebase Realtime Database, dan Progressive Web App. Data jarak ultrasonik dikonversi menjadi estimasi persentase pengisian, volume, dan massa melalui trimmed median filtering tujuh sampel, adaptive exponential smoothing dengan alpha dinamis 0,35–0,85, serta kalibrasi linear dua titik. Prototipe diuji pada lima kondisi pengisian utama, yaitu 0%, 13%, 45%, 87%, dan 100%, serta sweep tambahan dari 5% hingga 100%. Hasil pengujian menunjukkan pembacaan yang konsisten antara display OLED dan aplikasi web, dengan median respons antarmuka sebesar 1600,5 ms. Sistem juga mengelompokkan kondisi silo menjadi AMAN, SEDANG, HAMPIR HABIS, dan HABIS. Temuan ini menunjukkan bahwa SiloSense layak sebagai pendekatan monitoring non-kontak berbiaya rendah untuk estimasi level silo biji jagung skala kecil, dengan kebutuhan validasi lanjutan sebelum penerapan industri.



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Abstract. The availability of corn grain in production silos is important for maintaining the continuity of corn flour production. However, manual level inspection is discontinuous, requires operator involvement, and is prone to reading errors. This study presents SiloSense, an Internet of Things (IoT)-based corn grain silo level monitoring prototype using an HC-SR04 ultrasonic sensor, ESP8266 WeMos D1 Mini, SSD1306 OLED display, Firebase Realtime Database, and Progressive Web App. Ultrasonic distance data are converted into estimates of fill percentage, volume, and mass through seven-sample trimmed median filtering, adaptive exponential smoothing with a dynamic alpha range of 0.35–0.85, and two-point linear calibration. The prototype was tested under five main fill conditions, namely 0%, 13%, 45%, 87%, and 100%, along with an additional sweep from 5% to 100%. The results showed consistent readings between the OLED display and the web application, with a median interface response time of 1600.5 ms. The system also classifies silo conditions into SAFE, MODERATE, NEARLY EMPTY, and EMPTY. These findings indicate that SiloSense is feasible as a low-cost, non-contact monitoring approach for small-scale corn grain silo level estimation, with further validation required before industrial deployment.

1. INTRODUCTION

Corn grain storage plays an important role in maintaining the continuity of corn flour production. In production environments, the availability of raw material inside a silo must be monitored continuously because inaccurate stock information may affect production planning, material handling, and operational response [1], [2]. Conventional level inspection is commonly performed through direct observation or manual checking by operators. Although this approach is simple, it is discontinuous, labor-intensive, and prone to reading errors, particularly when the silo condition changes during production activities [3].

Recent developments in embedded systems and the Internet of Things (IoT) have enabled monitoring systems that can acquire sensor data, process measurements locally, and transmit information to cloud-based platforms in real time. In agricultural and industrial storage applications, IoT-based monitoring is useful because it reduces dependence on manual inspection and allows operators to observe system conditions remotely. A practical silo monitoring system should therefore combine sensing, local visualization, remote data synchronization, and operational status classification to support early decision-making [4], [5].

Level measurement in silos can be implemented using several sensing principles, including capacitive, load-cell, optical, radar, and ultrasonic methods. Among these alternatives, ultrasonic sensing is attractive for small-scale prototypes because it offers non-contact measurement, simple hardware integration, and compatibility with microcontroller-based systems. The HC-SR04 ultrasonic sensor estimates distance by measuring the time required for an emitted sound pulse to travel to the material surface and return to the receiver. However, applying ultrasonic sensing to granular materials such as corn grain is not always straightforward. The irregular surface of grain, local slope variation, and measurement outliers may cause unstable readings if the raw sensor output is used directly [6], [7].

Several previous studies have developed IoT-based monitoring systems using ultrasonic sensors and microcontrollers for liquid tanks,

material storage, and industrial automation. These systems demonstrate that low-cost hardware can be integrated with wireless communication and web-based visualization. However, many existing prototypes mainly focus on data acquisition and online display, while signal stabilization, calibration, multi-parameter estimation, and operational categorization are often treated as secondary components. For corn grain silo monitoring, this creates a research gap: a prototype system is needed that not only measures distance, but also processes unstable ultrasonic readings, converts them into meaningful fill information, and presents the results consistently through both local and remote interfaces.

To address this gap, this study presents SiloSense, an IoT-based corn grain silo level monitoring prototype using an HC-SR04 ultrasonic sensor, ESP8266 WeMos D1 Mini, SSD1306 OLED display, Firebase Realtime Database, and Progressive Web App. The proposed system converts ultrasonic distance data into fill percentage, volume, and mass estimates through seven-sample median filtering, adaptive exponential smoothing, and two-point linear calibration. The system also classifies silo conditions into SAFE, MODERATE, NEARLY EMPTY, and EMPTY to support early operational awareness. The main contribution of this study is the design and evaluation of a non-contact IoT monitoring prototype that integrates sensor processing, local display, real-time cloud synchronization, and operational status classification for small-scale corn grain silo level estimation.

2. LITERATURE REVIEW

Recent studies in smart agriculture and industrial IoT show that connected monitoring systems are increasingly used to support continuous sensing, embedded data processing, wireless communication, and remote visualization. In agricultural production environments, this architecture is relevant because material availability and storage conditions need to be observed continuously to support operational planning and early response. Recent work on precision agriculture also indicates that sensing and communication technologies are becoming central components of data-driven agricultural systems [8], [9]. However, IoT-based monitoring is not only a

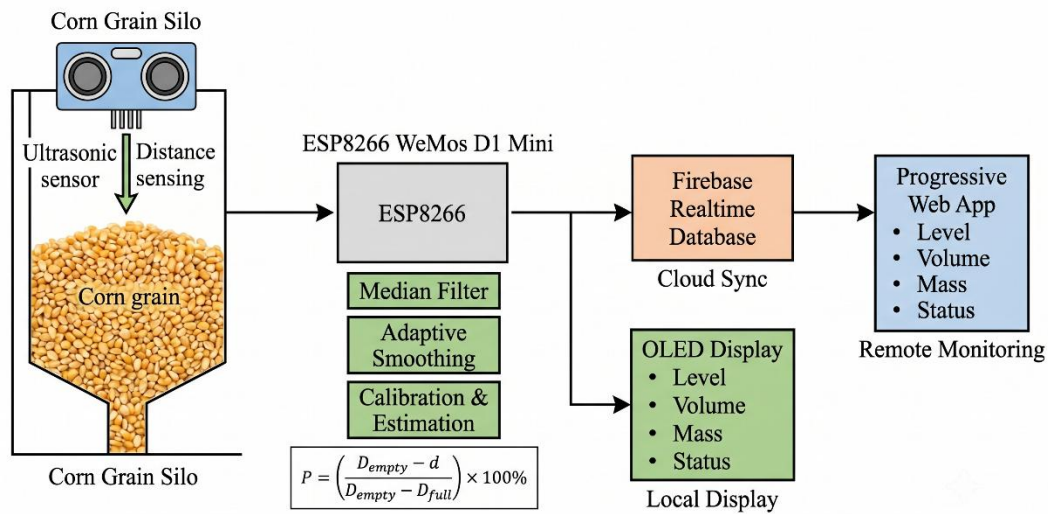


Figure 1. Overall architecture of the SiloSense corn grain silo level monitoring system.

matter of transmitting sensor data to a cloud platform; the reliability of sensor readings, data quality, and consistency between local and remote interfaces are also critical before the information can be used for operational decision-making [10].

Material level monitoring can be implemented using several sensing approaches, including load-cell, capacitive, optical, radar, and ultrasonic methods. For a small-scale prototype, ultrasonic sensing is a practical option because it enables non-contact measurement and simple integration with microcontroller-based IoT systems [11], [12]. Nevertheless, applying ultrasonic sensing to granular materials such as corn grain remains challenging because uneven grain surfaces, local slope variations, and irregular acoustic reflections may produce unstable distance readings. Therefore, a silo monitoring prototype should not only acquire and display raw sensor values, but also include measurement stabilization, calibration, parameter conversion, and operational status classification. Based on this gap, SiloSense integrates HC-SR04 ultrasonic sensing, embedded signal processing, Firebase-based synchronization, local OLED visualization, and Progressive Web App monitoring for small-scale corn grain silo level estimation [13].

3. RESEARCH METHOD

3.1. System Design

This study developed SiloSense as an IoT-based prototype for monitoring the level of corn grain in a small-scale silo model. The system

was designed using four main layers: sensing, embedded processing, local visualization, and remote monitoring. The sensing layer uses an HC-SR04 ultrasonic sensor installed at the top of the silo prototype and directed vertically toward the corn grain surface. The embedded processing layer uses an ESP8266 WeMos D1 Mini to acquire ultrasonic distance data, process the measurement, estimate the fill percentage, volume, and mass, and determine the operational status of the silo. The local visualization layer uses an SSD1306 OLED display to show the monitoring result near the prototype, while the remote monitoring layer uses Firebase Realtime Database and a Progressive Web App to display updated silo information through a web-based interface.

Table 1. Hardware components and functions of the SiloSense prototype

Component	Specification	Function
ESP8266 WeMos D1 Mini	3.3 V logic, Wi-Fi 802.11 b/g/n, 80 MHz	Main processing and IoT communication unit
HC-SR04 ultrasonic sensor	5 V DC, 2-400 cm range, ± 3 mm nominal accuracy	Non-contact distance and level measurement
SSD1306 OLED display	0.96 inch, 128×64 pixels, I2C interface	Local real-time display
Firebase Realtime Database	Cloud-hosted JSON database	Data storage and real-time synchronization
Silo prototype	Transparent plastic tube, 450 ml container capacity	Corn grain storage model
SiloSense web application	Progressive Web App	Remote monitoring interface

The prototype was built using a transparent plastic silo model with a physical container capacity of 450 ml. For the measurement reference, the effective maximum grain volume was set to 400 ml, corresponding to 340 g of corn grain. Two calibration points were used to convert the measured distance into the fill level: the full condition was defined at 3.90 cm from the sensor, while the empty condition was defined at 12.50 cm from the sensor. These values were used as the reference boundaries for calculating the fill percentage.

Table 2. Reference capacity and calibration parameters

Parameter	Value
Effective maximum volume	400 ml
Maximum corn grain mass	340 g
Full calibration distance	3.90 cm
Empty calibration distance	12.50 cm
Firestore update interval	1 s
Main program loop interval	±80 ms

3.2. Hardware Configuration

The hardware configuration consists of an HC-SR04 ultrasonic sensor, an ESP8266 WeMos D1 Mini, and an SSD1306 OLED display. The HC-SR04 sensor was installed at the upper part of the silo prototype and directed toward the corn grain surface to obtain non-contact distance measurements. The ESP8266 WeMos D1 Mini served as the main processing and communication unit, while the OLED display provided local visualization of the measured level, estimated volume, estimated mass, and silo status. The ESP8266 and OLED module were placed in a separate control box, while the ultrasonic sensor was mounted above the silo to maintain a fixed measurement position.

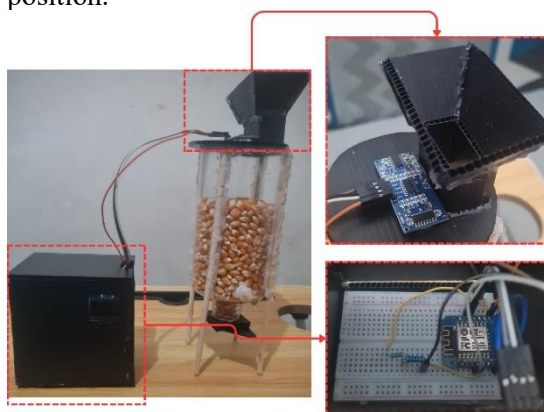


Figure 2. Physical implementation of the SiloSense prototype.

The sensor and display modules were connected to the ESP8266 through digital and I2C interfaces. The HC-SR04 TRIG and ECHO pins were connected to D5 and D6, respectively. The OLED display used the I2C interface, with SDA connected to D2 and SCL connected to D1. The complete wiring configuration is summarized in Table 3.

Table 3. Hardware wiring configuration

Module pin	ESP8266 pin	Description
HC-SR04 VCC	5 V	Sensor power supply
HC-SR04 GND	GND	Ground connection
HC-SR04 TRIG	D5	Ultrasonic trigger signal
HC-SR04 ECHO	D6	Ultrasonic echo signal
OLED VCC	3.3 V	Display power supply
OLED GND	GND	Ground connection
OLED SDA	D2	I2C data line
OLED SCL	D1	I2C clock line

3.3. Measurement and Signal Processing Algorithm

The measurement algorithm was designed to stabilize ultrasonic readings before converting them into silo level information. The overall measurement and signal processing workflow is shown in Figure 3.

The HC-SR04 sensor measures the distance between the sensor and the corn grain surface based on the time-of-flight principle. The distance is calculated using:

$$d = \frac{(v \times t)}{2} \quad (1)$$

where d is the measured distance, v is the speed of sound in air, and t is the round-trip travel time of the ultrasonic pulse.

Each measurement cycle collected seven consecutive distance samples. The samples were sorted, the two highest and two lowest values were removed, and the average of the three middle values was used as the filtered distance. This median-based trimmed filtering step was applied to reduce the influence of outliers caused by irregular acoustic reflections from the granular corn surface. In addition, sudden spikes larger than 2.5 cm were ignored to prevent unrealistic changes from affecting the displayed result.

The filtered distance was then processed using adaptive exponential smoothing. The smoothing equation is expressed as:

$$S_k = \alpha S_{(k-1)} + (1 - \alpha)x_k \quad (2)$$

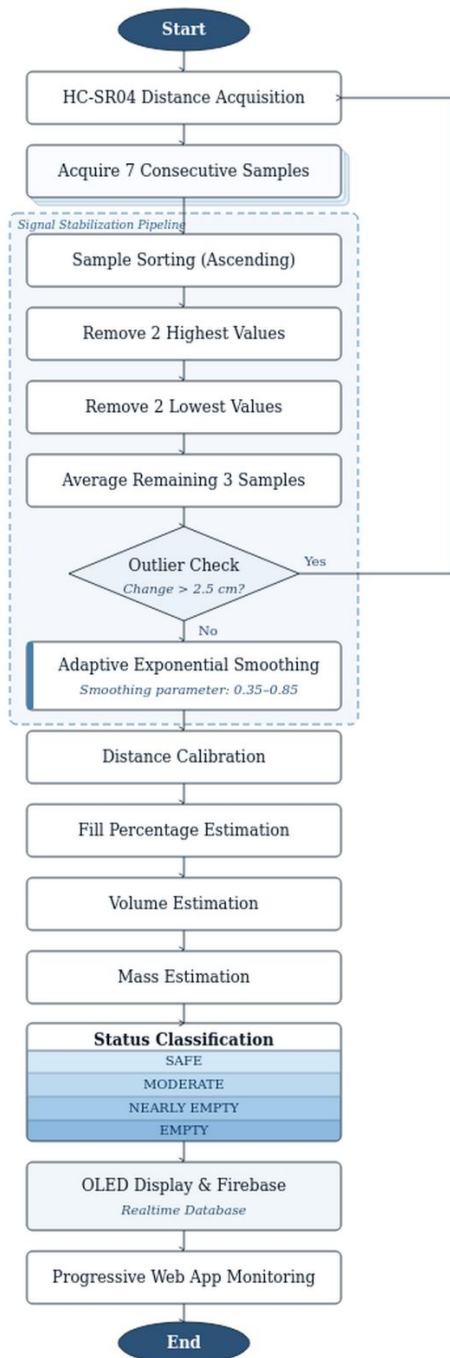


Figure 3. Signal processing workflow used in the SiloSense monitoring system.

where S_k is the smoothed distance at the current cycle, $S_{(k-1)}$ is the previous smoothed distance, x_k is the current filtered distance, and α is the smoothing coefficient. The value of α was dynamically selected based on the magnitude of distance change. A larger α was used for stable conditions to produce smoother readings, while a smaller α was used when larger changes occurred to improve response speed.

Table 4. Adaptive smoothing parameter configuration

Distance change	Alpha value	Effect
< 0.5 cm	0.85	Very smooth and stable during fixed level conditions
0.5-1.5 cm	0.60	Moderate response
> 1.5 cm	0.35	More responsive to rapid level changes

After filtering and smoothing, the measured distance was converted into fill percentage using a two-point linear calibration model:

$$P = \left(\frac{D_{empty} - d}{D_{empty} - D_{full}} \right) \times 100\% \quad (3)$$

where P is the fill percentage, D_{empty} is the empty calibration distance, D_{full} is the full calibration distance, and d is the current smoothed distance. The calculated percentage was limited to the range of 0-100%. The fill percentage was then converted into volume and mass estimates using the reference capacity of the prototype:

$$V = \left(\frac{P}{100} \right) \times V_{max} \quad (4)$$

$$M = \left(\frac{P}{100} \right) \times M_{max} \quad (5)$$

where V is the estimated volume, M is the estimated mass, V_{max} is the maximum reference volume of 400 ml, and M_{max} is the maximum reference mass of 340 g.

3.4. Operational Status Classification

The system classified the silo condition into four operational status categories based on the calculated fill percentage. This classification was used to make the monitoring output easier to interpret by operators. The status categories were SAFE, MODERATE, NEARLY EMPTY, and EMPTY.

Table 5. Operational status classification

Fill percentage	Status	Description
$\geq 70\%$	SAFE	Sufficient stock
30-69%	MODERATE	Stock should be monitored
1-29%	NEARLY EMPTY	Refilling is recommended
0%	EMPTY	Silo is empty

3.5. Firebase Integration and Web Monitoring

The processed monitoring data were sent from the ESP8266 to Firebase Realtime Database through a Wi-Fi connection. The

database stored seven main parameters: fill percentage, estimated volume, estimated mass, measured distance, full calibration point, empty calibration point, and silo status. Data transmission to Firebase was performed every one second to maintain real-time monitoring while avoiding excessive update frequency. The Progressive Web App retrieved data from Firebase and displayed the latest silo condition on a smartphone or web browser. This integration enabled the same monitoring result to be observed through both the local OLED display and the remote web application.

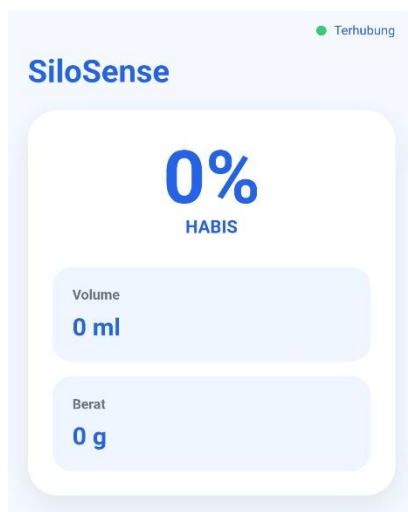


Figure 4. Data flow from ultrasonic sensing and ESP8266 processing to Firebase synchronization and Progressive Web App monitoring.

3.6. Experimental Procedure

The prototype was evaluated using five representative fill conditions: 0%, 13%, 45%, 87%, and 100%. These conditions were selected to represent empty, nearly empty, moderate, safe, and full silo levels. At each condition, corn grain was added to the prototype silo, and the system output was observed through both the OLED display and the Progressive Web App. The evaluation focused on three aspects: the conversion of ultrasonic distance into fill percentage, volume, and mass; the consistency between local and remote monitoring interfaces; and the correctness of operational status classification based on the predefined threshold values. The results of these tests are presented and discussed in Section 4.

4. RESULTS AND DISCUSSION

4.1. Prototype Implementation and Monitoring Interface

The SiloSense prototype was implemented by integrating the HC-SR04 ultrasonic sensor, ESP8266 WeMos D1 Mini, SSD1306 OLED display, Firebase Realtime Database, and Progressive Web App. The ultrasonic sensor was mounted at the top of the silo prototype to measure the distance between the sensor and the corn grain surface. The ESP8266 processed the measured distance into fill percentage, volume, mass, and operational status. The processed data were displayed locally through the OLED display and transmitted to Firebase for remote visualization through the web application.



Figure 5. Progressive Web App interface for real-time SiloSense monitoring.

The monitoring interface was designed to present the main operational parameters in a compact format, including fill percentage, estimated volume, estimated mass, and silo status. This design allows users to interpret the silo condition without manually converting sensor distance into storage information. The same processed values were used for both the local OLED display and the web interface, so that local and remote monitoring outputs remained consistent.

4.2. Representative Fill-Level Testing

The prototype was first evaluated using five representative fill conditions: 0%, 13%, 45%, 87%, and 100%. These conditions were selected to represent the main operational states of the silo, namely empty, nearly empty, moderate,

safe, and full conditions. The results are summarized in Table 6.

Table 6. Representative fill-level testing results of the SiloSense prototype

Condition	Fill percentage	Volume (ml)	Mass (g)	Status
Empty	0%	0	0	EMPTY
Nearly empty	13%	53	45	NEARLY EMPTY
Moderate	45%	181	154	MODERATE
Safe	87%	348	296	SAFE
Full	100%	400	340	SAFE

The results show that the system successfully converted the measured ultrasonic distance into interpretable storage information. At the empty condition, the system produced 0 ml and 0 g with an EMPTY status. At 13%, the system estimated 53 ml and 45 g, which was categorized as NEARLY EMPTY. This status is important because it can serve as an early refill indication for operators. At 45%, the system produced 181 ml and 154 g with a MODERATE status, indicating that material was still available but required attention. At 87% and 100%, the system categorized the silo as SAFE because the estimated fill level was above the safe threshold.

The volume and mass values follow the reference capacity used in the system design. The maximum reference volume was 400 ml and the maximum reference mass was 340 g. Therefore, the calculated values increase proportionally with the fill percentage. This confirms that the two-point calibration model can transform raw distance measurement into operational information that is easier to understand than distance values alone.

4.3. Expanded Fill-Level Sweep and Interface Response

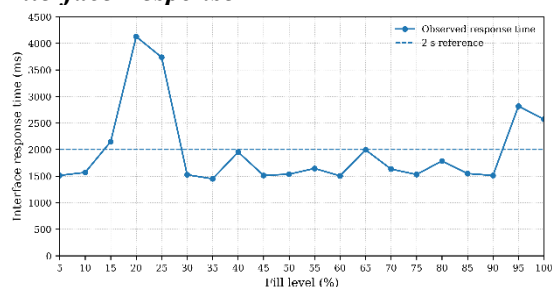


Figure 6. Interface response time across the expanded fill-level sweep of the SiloSense web monitoring system.

In addition to the five representative conditions, an expanded fill-level sweep was conducted from 5% to 100% with 5% increments. This additional test was used to observe whether the conversion model remained consistent across a wider operating range and to evaluate the response time of the web-based interface. The interface response time was recorded in milliseconds during the monitoring process.

Table 7. Summary of expanded fill-level sweep and interface response time

Parameter	Result
Fill-level range	5%–100%
Fill-level interval	5%
Number of test points	20
Reference volume range	20–400 ml
Reference mass range	17–340 g
Minimum interface response time	1449 ms
Median interface response time	1600.5 ms
Mean interface response time	1980.4 ms
Maximum interface response time	4127 ms
Test points updated within 2 s	15/20
Test points updated within 3 s	18/20

The expanded test shows that the monitoring system operated across the full measurement range of the prototype. The estimated volume and mass followed the proportional conversion model defined in the methodology. For example, a 50% fill condition corresponds to approximately 200 ml and 170 g, while a 100% fill condition corresponds to 400 ml and 340 g. This conversion makes the monitoring output more informative because users can directly observe the estimated amount of stored material rather than only viewing the fill percentage.

The interface response time ranged from 1449 ms to 4127 ms, with a median value of 1600.5 ms and an average value of 1980.4 ms. Most test points were updated within approximately two seconds, while two test points showed response times above three seconds. This indicates that the one-second Firebase update interval should be interpreted as the configured data transmission interval, while the actual interface response time may vary depending on Wi-Fi stability, Firebase synchronization delay, and client-side rendering conditions. Therefore, the system can be considered functional for near-real-time monitoring, but not yet suitable for applications that require strict deterministic latency.

4.4. Local and Remote Monitoring Consistency

The system was also evaluated by comparing the information shown on the OLED display and the Progressive Web App. The same processed data were sent to both interfaces, including fill percentage, volume, mass, and status. During testing, the values displayed on the local OLED and the web interface were consistent for each tested fill condition.

Table 8. Functional validation of local and remote monitoring interfaces

Evaluated aspect	OLED display	Progressive Web App	Result
Fill percentage	Available	Available	Consistent
Volume estimation	Available	Available	Consistent
Mass estimation	Available	Available	Consistent
Status classification	Available	Available	Consistent
Monitoring update	Local update	Firestore-based update	Functional

This consistency is important because the proposed system is intended to function as both a local measuring device and a remote IoT monitoring tool. The OLED display supports direct observation near the prototype, while the Progressive Web App enables users to observe the silo condition remotely through a smartphone or browser. By using the same processed data source, the system reduces the possibility of mismatch between local and remote monitoring outputs.

4.5. Discussion of Signal Processing and Operational Status

The signal processing stages contributed to improving the stability and interpretability of the monitoring output. The seven-sample trimmed median filtering reduced the influence of abnormal readings by sorting the measured samples, removing the two highest and two lowest values, and averaging the remaining three middle values. This approach is suitable for ultrasonic measurement on granular materials because corn grain surfaces are not perfectly flat and may produce irregular acoustic reflections.

Adaptive exponential smoothing further stabilized the displayed value by adjusting the smoothing coefficient according to the magnitude of distance change. Under stable conditions, a higher alpha value was used to

reduce small fluctuations in the displayed output. When a larger distance change occurred, a lower alpha value allowed the system to respond more quickly. This behavior is useful for silo monitoring because the system must remain stable when the fill level is constant, but still responsive when the silo is being filled or emptied.

The operational status classification also improved the practical usability of the system. Instead of requiring users to manually interpret numerical values, the system grouped the silo condition into SAFE, MODERATE, NEARLY EMPTY, and EMPTY. This classification provides a simple early-awareness mechanism for operators. For example, the 13% condition was categorized as NEARLY EMPTY, indicating that refilling should be considered, while the 87% and 100% conditions were categorized as SAFE.

4.6. Practical Implications and Limitations

The results indicate that SiloSense is feasible as a low-cost, non-contact monitoring prototype for small-scale corn grain silo level estimation. The non-contact characteristic of the HC-SR04 sensor is beneficial because the sensor does not physically touch the stored grain. This reduces the risk of material contamination and avoids mechanical interference between the sensor and the grain [14], [15], [16]. In addition, the ESP8266 and Firebase integration allows the monitoring result to be accessed remotely without requiring a dedicated local server.

However, the current evaluation should be interpreted as a prototype-level functional validation rather than a certified metrological accuracy test. The prototype used a small transparent silo model with a maximum reference volume of 400 ml and a maximum reference mass of 340 g. The test was conducted under controlled laboratory conditions and did not yet represent the complexity of industrial silo environments. Factors such as dust, temperature variation, non-uniform grain surface geometry, larger measurement distances, sensor mounting angle, and network instability may affect system performance in real deployment [17].

Therefore, further work is required before industrial implementation. Future validation should include repeated measurements at each fill level, comparison with reference

measurement instruments, larger silo dimensions, continuous filling and emptying scenarios, and environmental disturbance testing. For industrial-scale applications, higher-grade non-contact sensors such as radar or guided-wave radar may also be considered when longer range, higher robustness, and stronger dust tolerance are required [18], [19], [20].

5. CONCLUSION

This study developed SiloSense, an IoT-based corn grain silo level monitoring prototype using an HC-SR04 ultrasonic sensor, ESP8266 WeMos D1 Mini, SSD1306 OLED display, Firebase Realtime Database, and Progressive Web App. The system converts ultrasonic distance measurements into fill percentage, estimated volume, estimated mass, and operational status through trimmed median filtering, adaptive exponential smoothing, and two-point linear calibration.

The prototype functioned consistently across representative fill conditions of 0%, 13%, 45%, 87%, and 100%, corresponding to EMPTY, NEARLY EMPTY, MODERATE, and SAFE categories. The expanded 5%–100% fill-level sweep showed proportional volume and mass estimation, while the web interface response time ranged from 1449 ms to 4127 ms with a median of 1600.5 ms. These results indicate that SiloSense is feasible for small-scale non-contact silo level monitoring, although further validation using larger silos, repeated trials, and reference instruments is required before industrial deployment.

REFERENCE

- [1] A. N. Arun *et al.*, “Ambient IoT: Communications enabling precision agriculture,” *IEEE Commun. Mag.*, vol. 63, no. 4, pp. 137–143, Apr. 2025.
- [2] P. Ferrer-Cid, J. M. Barcelo-Ordinas, and J. Garcia-Vidal, “A review of graph-powered data quality applications for IoT monitoring sensor networks,” *J. Netw. Comput. Appl.*, vol. 236, no. 104116, p. 104116, Apr. 2025.
- [3] M. Sophocleous *et al.*, “A stand-alone, in situ, soil quality sensing system for precision agriculture,” *IEEE Trans. Agri. Elect.*, vol. 2, no. 1, pp. 43–50, Mar. 2024.
- [4] A. K. Arika Karpina and V. A. Veri arinal, “PROTOTIPE SMART HEALTH MONITORING UNTUK DETEKSIKECEMASAN BERBASIS INTERNET OF THINGS DENGAN METODE FUZZY LOGIC MENGGUNAKAN NODEMCU ESP32,” *J. Inform. dan Tek. Elektro Terap.*, vol. 13, no. 3S1, Oct. 2025.
- [5] A. D. Maharani, “Optimizing air pressure to improve the efficiency of bottle and can waste pressing on pneumatic machines,” *J. Inform. dan Tek. Elektro Terap.*, vol. 13, no. 3S1, Oct. 2025.
- [6] R. Alamsyah, E. Ryansyah, and R. Permana Andari Yasinta and Mufidah, “SISTEM PENYIRAMAN TANAMAN OTOMATIS MENGGUNAKAN LOGIKA FUZZY DENGAN TEKNOLOGI INTERNET OF THINGS BERBASIS ESP8266 DAN APLIKASI BLYNK,” *J. Inform. dan Tek. Elektro Terap.*, vol. 12, no. 2, Apr. 2024.
- [7] S. Marios and J. Georgiou, “Precision agriculture: Challenges in sensors and electronics for real-time soil and plant monitoring,” in *2017 IEEE Biomedical Circuits and Systems Conference (BioCAS)*, IEEE, Oct. 2017.
- [8] K. Sharma, “Integrating artificial intelligence and Internet of Things (IoT) for enhanced crop monitoring and management in precision agriculture,” *Sensors Int.*, vol. 5, 2024, doi: 10.1016/j.sintl.2024.100292.
- [9] A. Morchid, “Applications of internet of things (IoT) and sensors technology to increase food security and agricultural Sustainability: Benefits and challenges,” *Ain Shams Eng. J.*, vol. 15, no. 3, 2024, doi: 10.1016/j.asej.2023.102509.
- [10] S. F. Ahmed, “Insights into Internet of Medical Things (IoMT): Data fusion, security issues and potential solutions,” *Inf. Fusion*, vol. 102, 2024, doi: 10.1016/j.inffus.2023.102060.
- [11] K. C. Rath, “The Role of Internet of Things (IoT) Technology in Industry 4.0 Economy,” *Adv. Iot Technol. Appl. Ind. 4 0 Digit. Econ.*, pp. 1–28, 2024, doi: 10.1201/9781003434269-1.
- [12] F. Fuentes-Peñailillo, “Transformative Technologies in Digital Agriculture: Leveraging Internet of Things, Remote Sensing, and Artificial Intelligence for Smart Crop Management,” *J. Sens. Actuator Networks*, vol. 13, no. 4, 2024, doi: 10.3390/jsan13040039.
- [13] A. Ullah, “Smart cities: the role of Internet of Things and machine learning in realizing a data-centric smart environment,” *Complex Intell. Syst.*, vol. 10, no. 1, pp. 1607–1637, 2024, doi: 10.1007/s40747-023-01175-4.
- [14] Y. Hu, “Industrial Internet of Things

- Intelligence Empowering Smart Manufacturing: A Literature Review,” *IEEE Internet Things J.*, vol. 11, no. 11, pp. 19143–19167, 2024, doi: 10.1109/JIOT.2024.3367692.
- [15] B. A. Odilov, “Utilizing Deep Learning and the Internet of Things to Monitor the Health of Aquatic Ecosystems to Conserve Biodiversity,” *Nat. Eng. Sci.*, vol. 9, no. 1, pp. 72–83, 2024, doi: 10.28978/nesciences.1491795.
- [16] F. Oliveira, “Internet of Intelligent Things: A convergence of embedded systems, edge computing and machine learning,” *Internet of Things Netherlands*, vol. 26, 2024, doi: 10.1016/j.iot.2024.101153.
- [17] F. C. Andriulo, “Edge Computing and Cloud Computing for Internet of Things: A Review,” *Informatics*, vol. 11, no. 4, 2024, doi: 10.3390/informatics11040071.
- [18] G. Moloudian, “RF Energy Harvesting Techniques for Battery-Less Wireless Sensing, Industry 4.0, and Internet of Things: A Review,” *IEEE Sens. J.*, vol. 24, no. 5, pp. 5732–5745, 2024, doi: 10.1109/JSEN.2024.3352402.
- [19] O. Aouedi, “A Survey on Intelligent Internet of Things: Applications, Security, Privacy, and Future Directions,” *IEEE Commun. Surv. Tutorials*, vol. 27, no. 2, pp. 1238–1292, 2025, doi: 10.1109/COMST.2024.3430368.
- [20] A. D. Dwivedi, “Blockchain and artificial intelligence for 5G-enabled Internet of Things: Challenges, opportunities, and solutions,” *Trans. Emerg. Telecommun. Technol.*, vol. 35, no. 4, 2024, doi: 10.1002/ett.4329.