

## Advances in Machine Learning for Real-Time Monitoring and Evaluation of Grain Storage Facilities: A Survey

Usha K. Patil<sup>1,2</sup> Prashanth M V<sup>2</sup>

<sup>1</sup>Department of Computer Science & Engineering, National Institute of Engineering, Mysuru, India

<sup>2</sup>Department of Computer science & Engineering (AIML), Vidya Vardhaka College of Engineering, Mysuru, India (Autonomous Institution affiliated to Visvesvaraya Technological University, Belagavi)

ushakpatil@nie.ac.in, prashanthmv@vvce.ac.in

\*Corresponding author: ushakpatil@nie.ac.in

### Abstract

Grain storage loss prevention is one of the critical challenges in ensuring food security due to rising global demand and climate change. Conventional storage monitoring methods are often manual, error-prone, and inefficient and often resulting in large quantitative and qualitative losses. Rapid developments in real-time sensing technologies, Machine Learning (ML) and the Internet of Things (IoT) have enabled intelligent grain storage monitoring systems capable of detecting abnormalities, predicting spoilage, and supporting decision-making processes. This paper presents a full review of existing research on real-time grain storage monitoring using ML techniques. It categorizes and analyzes the studies based on the monitored parameters like humidity, temperature, gas emissions etc., technological frameworks such as IoT, cloud, edge computing, and applied ML algorithms like CNN, SVM, Random Forest. Strengths, limitations, and practical constraints of each approach are discussed, along with identified research gaps in data quality, system scalability, and model generalization. Furthermore, the paper explores implementation challenges in real-world scenarios and outlines future research directions such as federated learning, sensor fusion, and development of standardized datasets. The survey serves as a foundational reference for researchers, engineers, and policymakers working on smart, data-driven grain storage solutions.

**Keywords:** Real-time monitoring, Grain storage, Machine Learning, IoT, Quality assessment, Spoilage prediction.

### 1. Introduction

Grain storage is an essential component of the post-harvest supply chain that directly impacts global food security and agricultural sustainability[1]. With the increasing demands of a growing population, combined with the effects of climate change and global supply chain disruptions, minimizing post-harvest grain losses has become more critical than ever[2]. As per the Food and Agriculture Organization (FAO), almost one-third of the grains produced are wasted because of improper storage methods. This not only causes major financial losses for farmers but also adds to food shortages and harms the environment. [3].

Traditional grain storage facilities, including silos, warehouses, and godowns, often rely on manual inspection and passive storage techniques. These methods are inherently time-consuming, labor-intensive, and error-prone, making them inadequate for large-scale or long-term storage[4][5]. Environmental factors such as temperature, humidity, gas concentrations like CO<sub>2</sub>, NH<sub>3</sub>, and insect infestations are key contributors to grain spoilage, and they demand continuous and accurate monitoring to ensure quality preservation[6].

Recent advancements in real-time sensing, IoT and ML have revolutionized the way grain storage monitoring can be performed[7][8]. ML-based systems can analyze streaming sensor data, detect anomalies, predict spoilage events, and provide intelligent recommendations for corrective actions[9]. When integrated with IoT infrastructure, these systems enable automated, scalable, and remote monitoring capabilities, greatly reducing human intervention and operational costs[10][11].

This survey presents a comprehensive overview of state-of-the-art research in the field of real-time monitoring and evaluation of grain storage facilities using ML techniques[12]. The key objectives of this survey are:

- To examine the current landscape of grain storage monitoring systems using ML and IoT.
- To categorize existing works based on monitored parameters, applied ML models, and deployment scenarios.
- To provide a comparative analysis of these approaches based on performance metrics, accuracy, and limitations.
- To identify major challenges in practical deployment including data scarcity, sensor reliability, and model generalization.
- To propose future research directions for developing intelligent, sustainable, and scalable monitoring systems.

By summarizing and synthesizing current research trends, this survey aims to serve as a foundational reference for researchers, engineers, and policymakers involved in agricultural technology, post-harvest systems, and smart farming innovations.

### 2. Background Concepts

#### 2.1 Technologies for Monitoring

Modern grain storage monitoring systems utilize an array of sensors to capture real-time environmental and biological data [13]. These include temperature sensors that monitor internal heat buildup which often signals the microbial activity or spoilage [14], and humidity sensors that detect moisture levels responsible for fungal growth or grain germination [15]. Gas sensors are also deployed to measure concentrations of gases such as CO<sub>2</sub>, NH<sub>3</sub>, and ethylene, which indicate biological decomposition or insect respiration [16]. In addition, pressure and weight sensors help track grain levels for inventory management while also detecting settling or compaction [17]. Furthermore, specialized insect and mold detection sensors leveraging image recognition, acoustic signals, or pheromone traps are integrated with smart detectors to identify biological threats [18]. These sensing technologies ensure that critical parameters are logged in real time, forming the backbone of predictive analytics in grain storage.

#### 2.2 Overview of Machine Learning Techniques

Machine learning provides the computational intelligence required to analyze large volumes of sensor data and identify patterns indicative of spoilage or system failures [19]. In grain storage monitoring, several ML techniques are applied to enhance predictive accuracy and automation. Supervised learning models such as Support Vector Machines (SVM) [20] are effective for classification tasks like spoilage detection based on multiple sensor inputs, while Random Forest (RF) [21], as an ensemble method, is widely used for feature-rich datasets where both interpretability and accuracy are required. Artificial Neural Networks (ANN) [22] capture complex, non-linear relationships between environmental parameters such as temperature and humidity and the occurrence of spoilage events, whereas Convolutional Neural Networks (CNN) [23] are particularly suited for image-based pest detection and visual quality assessment of grains. In addition to supervised methods, unsupervised learning techniques are also employed, including clustering approaches such as K-Means and DBSCAN [24], which group data exhibiting similar spoilage patterns or anomalies without requiring labeled outputs, and anomaly detection methods [25], which identify deviations from normal sensor behavior to facilitate early detection of potential storage failures. Furthermore, time-series and deep learning models like Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) architectures [26] are applied to capture temporal dependencies in sensor data streams, enabling real-time forecasting of spoilage trends. Collectively, these models leverage both historical and real-time data to detect spoilage events, predict shelf life, and support automated decision-making in modern grain storage systems.

### 2.3 IoT in Agriculture

IoT in agriculture, or AgriTech IoT [27], refers to the integration of physical sensors, actuators, gateways, and cloud platforms to support data-driven farming and storage operations. In grain storage systems [28], sensor nodes [29] collect environmental data and transmit it through wireless networks such as Wi-Fi, Zigbee, or LoRa. The collected data is aggregated by gateways [30], which relay it to the cloud or local edge servers for further processing. Cloud platforms [31], including solutions like AWS and Azure IoT Hub, provide scalable storage, analytics, and alerting systems, while mobile and web dashboards [32] enable real-time visualization, alerts, and control actions by users. Together, these IoT components ensure seamless data acquisition, remote monitoring, and responsive automation, thereby laying the foundation for smart grain storage.

### 3. Literature Survey

This section examines key research in real-time monitoring and evaluation of grain storage facilities using Machine Learning (ML) and IoT technologies. It is organized by technology and application domains, highlighting both strengths and limitations.

#### 3.1 IoT-based Grain Monitoring Systems

Several IoT-enabled solutions have been developed for real-time monitoring of food grain storage. An automated monitoring system for warehouses [33] utilizes arrays of sensors to track environmental parameters such as temperature, humidity, vibration, CO, motion, and smoke, with data transmitted via GSM and cloud platforms. The system generates alerts when these parameters exceed threshold values. Another approach, an IoT-based real-time monitoring and control system for grain storage and procurement [34], uses DHT11 and gas sensors along with an exhaust fan mechanism to ensure that the grains are stored under ideal environmental conditions.. Similarly, an intelligent quality monitoring system [35] leverages temperature, humidity, and ammonia sensors to assess grain quality and communicates alarms through wireless links when deviations occur.

#### 3.2 AI & ML Augmented Solutions

AI and ML have also been employed to strengthen predictive analytics in grain storage. A multi-model fusion approach for temperature prediction [36] combines AdaBoost, decision trees, extra-trees, and Random Forest models, where ensemble fusion enhances accuracy and reveals significant influencing variables. Deep learning has further advanced this field, as demonstrated by a smart grain storage framework [37] that integrates 3D DenseNet with CNN-LSTM to monitor volumetric temperature distributions in silos and predict risks such as condensation and spoilage. In addition, electronic nose technologies [38] employing VOC sensor arrays and pattern classifiers have been investigated for pest detection in stored grains, with findings emphasizing accuracy improvements while also identifying persisting challenges.

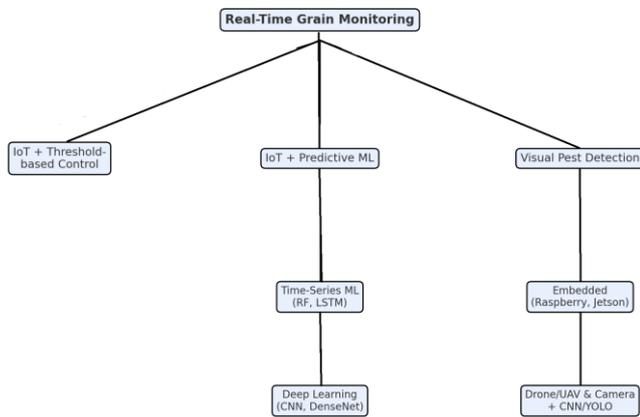
#### 3.3 Comparative Table of Selected Works

To provide a consolidated view of the current research landscape, Table 1. presents a comparative summary of selected works on IoT- and AI-enabled grain storage monitoring and management. The studies are organized chronologically and categorized by technology, sensing mechanisms, parameters monitored, machine learning techniques, and reported outcomes. This comparative perspective highlights the evolution from threshold-based monitoring systems toward advanced AI and blockchain-integrated frameworks. It also highlights recurring limitations such as lack of predictive capability, high implementation costs, restricted scalability, and dataset dependency. By synthesizing these findings, the table offers insights into both the maturity of existing solutions and the gaps that future research must address.

Table 1. Consolidated Summary of IoT- and ML-enabled Grain Storage Monitoring Systems

Category	Representative Studies	Technologies & Sensors	ML / AI Techniques	Key Contributions	Major Limitations
IoT-only & Rule-based Monitoring Systems	[39], [40], [41], [42], [43], [44], [45]	Temp, humidity, CO <sub>2</sub> , gas sensors, GSM, NodeMCU	Threshold logic, Kalman filter	Low-cost real-time monitoring and alerts	No prediction, static thresholds
Review & Survey Papers	[46], [47], [48], [49], [50], [52]	Literature-based (sensors, imaging, AI, traps)	Not applicable	Comprehensive overview of grain storage, pest control, and AI trends	No experimental validation
ML-based Environmental Prediction & Control	[53], [54]	IoT sensors, cloud/edge platforms	ResNet, ANN, Bayesian models	Spoilage prediction and intelligent ventilation control	High computational cost, data dependency
Computer Vision-based Pest Detection	[55], [56], [57], [58], [59]	Camera embedded traps, vision systems	CNN, YOLO variants	High pest detection accuracy (>95% mAP)	Dataset dependency, limited pest diversity
Gas / VOC & e-Nose-based Pest Detection	[60], [61], [62]	VOC sensors, e-nose, NIRS, HSI	SVR, GPR, PLSR	Early pest detection via volatile signatures	Sensor drift, calibration sensitivity
Multimodal & Advanced AI Frameworks	[63], [64], [65], [66]	Spectral imaging, IoT, blockchain, edge AI	DL, fusion models, federated learning	End-to-end intelligence and traceability	Infrastructure cost, interoperability
Energy-efficient & Sustainable Storage Systems	[67], [68]	Solar, PCM, renewable hybrid systems	Digital twin, optimization	Off-grid cooling and sustainable storage	No AI-based spoilage prediction

From the comparative analysis in Table 1, it is evident that research on automated diagnosis and monitoring has steadily evolved from conventional imaging and rule-based approaches toward deep learning and synthetic data augmentation strategies. While recent works demonstrate improved accuracy, robustness, and adaptability, challenges remain in terms of dataset standardization, interpretability of models, and deployment in real-world storage environments. Most studies rely on limited or proprietary datasets, making reproducibility and benchmarking difficult. Moreover, although synthetic data generation offers promise in addressing data scarcity, ensuring biological and environmental realism and regulatory acceptance remains an open issue. These observations highlight the need for future research to focus on developing standardized, large-scale datasets, explainable deep learning models, and experimentally validated frameworks that bridge the gap between research and practice.



**Figure 1.** Classification of Real-Time Grain Storage Monitoring Systems Integrating Machine Learning and IoT

The taxonomy of real-time grain storage monitoring systems that integrate IoT technologies with ML techniques is presented in Figure 1. The taxonomy categorizes existing approaches into three main classes: (1) IoT-based systems with threshold-based control, which rely on preset limits for environmental parameters to trigger alerts and actuations; (2) IoT-enabled systems with predictive machine learning, which use historical and real-time data to forecast spoilage risks or detect anomalies using algorithms such as Random Forest, LSTM, and deep neural networks; and (3) Computer vision-based pest detection systems, which apply convolutional neural networks (CNNs), YOLO models, or custom architectures on image data from embedded or drone-based cameras. This structured classification helps to differentiate between systems that offer basic monitoring and those capable of intelligent prediction and decision support. It also highlights the increasing trend toward embedded AI and edge computing for autonomous and scalable deployment.

### 3.4 Observations & Trends

The evolution of IoT- and AI-enabled grain storage monitoring systems reveals a steady shift from basic sensing to intelligent, multimodal solutions. Early research (2021–2022) focused primarily on threshold-based monitoring with temperature, humidity, and gas sensors. While effective for real-time sensing, these systems lacked predictive and decision-making capabilities. More recent studies (2023–2025) demonstrate growing adoption of ML and DL, significantly improving pest detection, spoilage prediction, and ventilation automation. A notable trend is the dominance of computer vision, particularly YOLO-based models, for pest identification. These architectures have achieved outstanding accuracy (often >99% mAP), addressing challenges beyond the reach of traditional threshold methods. Parallel developments include blockchain for traceability and edge computing for scalable, real-time operations, reflecting an emphasis on secure and distributed architectures.

Sensor diversity has also expanded. In addition to temperature and humidity, advanced modalities such as spectral, near-infrared, and hyperspectral imaging, VOC e-noses, and UV-based light traps are increasingly used. These multimodal systems capture richer biological and chemical signals, enabling early-warning capabilities. However, trade-offs persist: low-cost IoT prototypes enhance accessibility but often lack AI integration, while high-performance AI-driven solutions face challenges of cost, complexity, and limited generalizability across diverse grain types and environments. Recent literature also points to sustainability, with renewable-powered systems like solar-assisted cooling and hybrid energy solutions designed for off-grid contexts. Review papers further highlight future opportunities in digital twins, robotics, and augmented reality, though these often lack experimental validation.

Despite advances, challenges remain in interoperability, standardization, dataset diversity, and infrastructure costs. Overall, the trajectory reflects a transition from simple sensor-based systems toward intelligent, secure, and sustainable solutions, though scalability and real-world deployment hurdles must still be addressed.

### 3.5 Trends, Observations & Research Gaps

IoT-based systems continue to remain popular due to their affordability and real-time data acquisition capabilities. However, they predominantly rely on static threshold logic and simple automation, which limits their ability to perform dynamic anomaly detection, spoilage forecasting, or contextual analysis. In contrast, Machine Learning and Deep Learning approaches particularly those leveraging CNNs, LSTMs, ensemble methods, and attention mechanisms have demonstrated strong predictive accuracy for early detection of spoilage and pest infestation, as well as in recognizing complex patterns. Despite these advances, their adoption is often constrained by computational overhead, especially in edge computing or rural deployments where resources are limited. Another key limitation across existing literature is the lack of attention to explainability and interpretability of AI models. Few studies attempt to provide insights into how predictions or decisions are generated, which reduces trust and hinders adoption among agricultural practitioners and policymakers.

Additionally, sensor fusion and multimodal approaches remain underexplored. Although a few hybrid models integrate environmental, visual, and gas-sensing data, there is still no standardized framework for optimal data fusion, device calibration, or adaptive responses under changing storage conditions. A further challenge lies in the scarcity of benchmark datasets for grain storage, as most studies rely on proprietary datasets that are narrow in scope and fail to represent diverse grain types or real environmental noise. This lack of standardization makes fair comparisons across models difficult and reduces reproducibility. Moreover, limited focus has been given to robustness testing, generalization across grain varieties and climatic conditions, or sustainable deployment strategies such as energy-efficient models and offline-capable processing. Addressing these gaps is essential to ensure that intelligent grain storage monitoring systems can move beyond experimental prototypes and become practical, scalable solutions in real-world agricultural contexts.

## 4. Comparative Analysis

This section synthesizes 30 reviewed studies on real-time grain storage monitoring using ML, DL, and IoT technologies. The analysis is structured around themes, strengths and limitations, and persisting research gaps.

### 4.1 Common Themes & Trends

Most studies emphasize IoT-enabled sensing, where temperature and humidity are consistently tracked using low-cost sensors such as DHT11. These are frequently combined with CO<sub>2</sub>, VOC, or vibration sensors linked to microcontrollers or GSM/IoT modules for real-time monitoring. On the computational side, models span classical ML (SVM, Random Forest) to advanced DL, notably CNN, CNN-LSTM, and 3D DenseNet. CNN architectures dominate visual pest detection due to their strength in image recognition, while LSTM and hybrid fusion models capture temporal sensor patterns. Object detection frameworks, particularly YOLO variants, are applied for pest identification in

grains and orchard settings. Although temperature and humidity remain universal, advanced systems incorporate gas sensing, grain motion, and pest imagery for richer monitoring. Importantly, most solutions are application-specific, tailored to silo, warehouse, or grain-type contexts.

**4.2 Strengths**

IoT-based systems automate monitoring and reduce reliance on manual inspection, significantly improving preservation. Deep learning has further advanced accuracy, with CNN-LSTM approaches reporting prediction rates above 97% in spoilage and pest detection. Beyond algorithms, innovative sensor technologies broaden monitoring capabilities. E-nose systems that detect VOCs and 3D temperature arrays provide high-fidelity insights into spoilage and pest presence. Such advances extend monitoring beyond simple thresholding to more adaptive and intelligent solutions.

**4.3 Limitations**

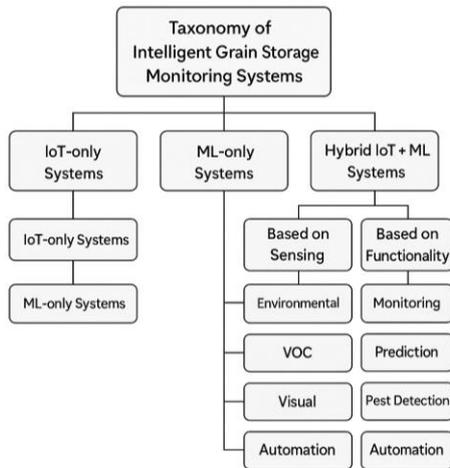
Despite progress, significant challenges remain. Computationally intensive models such as DenseNet and ensemble CNNs are unsuitable for rural or edge deployments due to high processing demands. Generalization is another limitation: many models are trained on narrow datasets, restricting their applicability across diverse grain types or environmental conditions. As a result, false positives or missed detections persist. Moreover, several studies continue to rely on static thresholding, as seen in the works of Lydia J. et al. and Mahadevaswamy et al., which restricts adaptability and predictive value in dynamic storage environments.

**4.4 Research Gaps**

Critical gaps persist across data, sensors, energy efficiency, and evaluation practices (Table 2). First, a lack of open-access labeled datasets hinders reproducibility and benchmarking across grain types and storage conditions. Second, limited sensor fusion restricts contextual insights, as most studies isolate temperature or humidity without integrating gas, motion, and image data. Third, lightweight and energy-efficient ML models suitable for solar-powered or offline use remain scarce, despite their necessity in rural deployments. Fourth, most ML integration remains offline; real-time prediction continues to be a bottleneck. Model explainability is also rarely addressed, reducing trust among stakeholders. Finally, the absence of standardized evaluation benchmarks makes it difficult to compare systems on accuracy, robustness, or scalability.

Table 2: Research Gaps

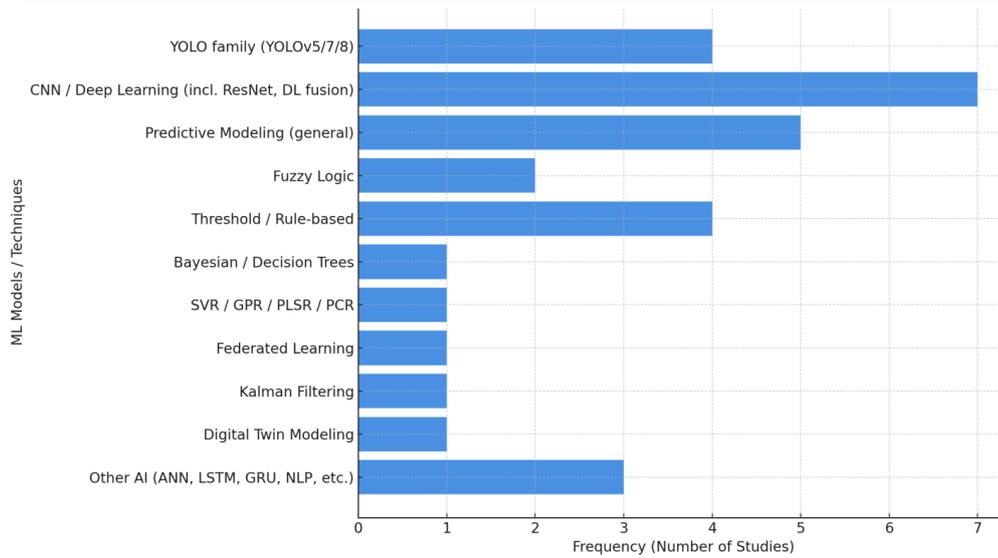
Category	Observed Gap
Dataset Availability	Few open-access, labeled datasets across grain types and environments
Sensor Fusion	Minimal fusion across gas, temperature, motion, and image data
Energy-efficient Deployment	Lack of lightweight models for solar-powered or offline operations
Real-time ML Prediction	ML is often run offline; real-time integration remains a bottleneck
Model Explainability	Very few models offer interpretable outputs or visualizations for decision trust
Standard Evaluation	No consistent benchmark to compare accuracy, robustness, or deployment success



**Figure 2:** Taxonomy of Intelligent Grain Storage Monitoring Systems

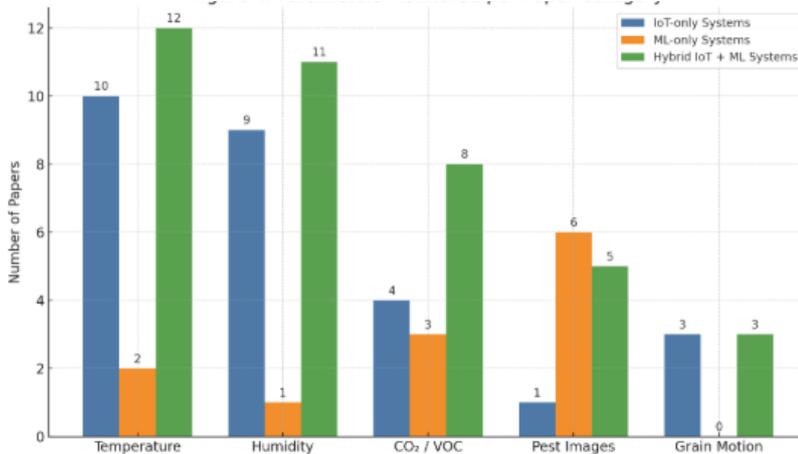
A comprehensive taxonomy of intelligent grain storage monitoring systems is shown in Figure 2. At the top level, the systems are categorized into three primary types: IoT-only systems, ML-only systems, and Hybrid IoT + ML systems.

Systems are categorized into IoT-only, ML-only, and Hybrid IoT+ML. Each is further subdivided by sensing type which are Environmental (temperature, humidity), VOC (gas sensing for pests), and Visual (image-based). These approaches enable functions ranging from real-time environmental tracking to predictive spoilage modeling, automated pest detection, and ventilation control. The taxonomy illustrates the field’s evolution from basic sensor networks to integrated solutions capable of real-time decision-making.



**Figure 3: ML Model Usage Frequency in Grain Storage Research**

The distribution of machine learning models and techniques applied in IoT and AI-enabled grain storage monitoring and management research is illustrated in Figure 3. Deep learning approaches, including CNN-based models and architectures such as ResNet which dominate the landscape and reflecting their effectiveness in handling multimodal data and complex feature extraction tasks. Object detection models particularly the YOLO family (YOLOv5, YOLOv7, YOLOv8-based variants) are also widely adopted for pest detection and visual monitoring due to their high accuracy and speed. Predictive modeling techniques appear frequently, though often in a generalized sense without specification of algorithms, underscoring their role in early warning systems and spoilage forecasting. Traditional approaches such as fuzzy logic, rule-based systems, and threshold-based monitoring remain relevant, particularly in low-cost or resource-constrained setups, while specialized methods like Bayesian learning, decision trees, federated learning, Kalman filtering, and digital twin modeling are less common but demonstrate the breadth of experimentation in this domain. Overall, the frequency distribution highlights a clear trend toward deep learning and object detection models, while classical and emerging AI techniques are used in niche applications or as complementary methods.



**Figure 4: Parameters Monitored per Paper Category**

The clustered column chart shown in Figure 4 visually compares the frequency with which key environmental and biological parameters are monitored across three categories of grain storage systems which are IoT-only, ML-only, and Hybrid IoT+ML solutions. Temperature and humidity dominate, especially in IoT-only and hybrid setups. Hybrid systems show the broadest coverage, integrating CO<sub>2</sub>/VOC sensing, pest imagery, and grain motion. ML-only studies emphasize visual pest detection through image analysis rather than multi-sensor data. This indicates that hybrid systems, which merge real-time IoT sensing with predictive ML, are the most versatile and promising direction for future development.

### 5. Challenges and Research Gaps

Despite notable advances in intelligent grain storage monitoring, several challenges hinder large-scale adoption. IoT-based systems often face irregular connectivity, sensor drift, and inconsistent sampling rates. Environmental fluctuations and hardware limitations reduce trust in real-time data, particularly in rural setups. Next challenge is, even though low cost sensors are economical, they suffer from calibration drift and environmental noise, leading to inaccurate readings of temperature, humidity, and gas concentrations. Standardized calibration and self-diagnosing mechanisms are rarely applied. Next challenge is, Most machine learning models are trained on localized datasets, limiting adaptability across grain types, climates, and storage infrastructures. This leads to false alarms or undetected anomalies, with little work on transfer learning or domain adaptation. Another challenge is, the scaling of intelligent systems is expensive due to sensor density, power management, and communication needs. Edge computing and on-device ML, crucial for rural scalability, remain nascent in this domain. Lastly, Publicly available datasets on spoilage, pest infestation, and multi-sensor conditions are scarce, limiting benchmarking and reproducibility.

Addressing these gaps requires interdisciplinary collaboration, hardware standardization, federated data sharing, explainable AI, and low-power edge ML models to enable robust, affordable, and scalable solutions.

## 6. Future Research Directions

The ongoing evolution of grain storage monitoring systems presents an exciting opportunity for researchers to address current limitations by adopting advanced technologies and frameworks. The following objectives are proposed to accelerate innovation in this domain.

1. Analysis of Grain Storage facilities and techniques in warehouse .
2. Designing the Test Bed for Automated Grain Monitoring system during Storage.
3. To provide Optimal solution to enhance the food safety and Quality using Machine Learning Techniques during Grain Storage

By following these research directions, future grain storage systems can evolve from reactive monitoring tools to proactive, intelligent platforms that support food security, minimize post-harvest losses, and contribute to sustainable agriculture at scale.

## 7. Conclusion

This survey comprehensively reviewed real-time grain storage monitoring systems integrating Machine Learning (ML) and Internet of Things (IoT) technologies. Here, Thirty representative studies were analyzed and systematically categorized based on sensing modalities, ML techniques, and functional objectives which includes environmental monitoring, spoilage prediction, pest detection, and decision support. The comparative and taxonomic analyses indicate that IoT-based systems are effective in continuous data acquisition, remote monitoring, and alert generation. However, they predominantly rely on threshold-based logic and lack predictive intelligence. In contrast, ML-driven approaches particularly the deep learning models such as CNNs, LSTMs, and YOLO-based architectures demonstrate superior performance in pest identification, spoilage forecasting, and automated control. But the computational complexity is higher and also there is a dependence on large, labeled datasets. The survey identifies critical research gaps, including unreliable real-time data streams with limited model generalization across diverse storage environments. There is also lack of standardized open datasets, insufficient sensor fusion, and weak integration between sensing, analytics, and autonomous decision-making. Addressing these challenges through scalable, energy-efficient, and interpretable AI models, coupled with robust IoT infrastructures and standardized benchmarking practices, is essential for transitioning from experimental prototypes to deployable intelligent grain storage systems. Such advancements are vital for reducing post-harvest losses, improving food quality, and strengthening global food security.

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