AI-driven technologies for pest monitoring, unsound kernel detection, and intelligent aeration in grain storage

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Abstract: Grain storage plays a crucial role in safeguarding food security and maintaining market stability, and it has therefore attracted growing attention from both academia and industry. The primary objective of storage technologies is to minimize post-harvest losses caused by pests, mold, and mechanical damage. However, conventional storage management methods, which rely heavily on manual labor, are often inefficient and costly. With the rapid advancement of artificial intelligence (AI), various approaches, such as convolutional neural network (CNN)-based models, Transformer-based frameworks, and emerging Mamba architectures, have been introduced into the field of grain storage. This paper presents a comprehensive review of artificial intelligence methodologies applied across multiple stages of the grain storage process. From four complementary perspectives, including application significance, existing AI techniques, comparative analysis, and future development trends, the review systematically summarizes current progress in pest monitoring, unsound kernel detection, and intelligent aeration. It critically examines their respective advantages and limitations, while outlining key challenges and future research directions. The review aims to offer a global perspective on the integration of AI technologies in grain storage and to foster interdisciplinary collaboration toward the development of intelligent, efficient, and sustainable storage systems.

Keywords: smart grain storage, artificial intelligence, grain conditions monitoring
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1 Introduction

Grain is a fundamental resource essential for national development and human well-being. Given its cyclical production, grain storage plays a critical role in supporting stabilizing markets, responding to emergencies, and enhancing national security. The Food and Agriculture Organization of the United Nations (FAO) recommends that a country's static storage capacity should exceed its annual production capacity, thereby guaranteeing sufficient reserves to cope with emergencies and market fluctuations[1].

As global grain production continues to rise, the need for efficient postharvest management and modernized storage facilities has become increasingly urgent. However, many regions still suffer from a shortage of storage capacity, leading to higher costs and substantial losses along the supply chain. During long storage, grains are vulnerable to deterioration caused by biotic and abiotic factors, among which insects and molds are the most destructive, resulting in contamination, nutritional degradation, and economic loss[2,3].

Studies estimate that 10%-40% of stored grains can be lost due to insect damage alone, with even greater losses when mold contamination occurs[4]. Such issues not only threaten economic stability but also food safety and public health, highlighting the importance of developing intelligent and real-time monitoring technologies to safeguard grain quality and security[5-8].

Although various sensors are used to monitor different aspects of grain storage, there remains a lack of efficient methods for automatically integrating and analyzing sensor data to generate meaningful and timely insights or to control relevant machinery autonomously. These challenges arise primarily from the high dimensionality, strong coupling, nonlinearity, and temporal variability of grain storage data, as well as from the complexity of operational decision-making under uncertain environmental conditions. Artificial Intelligence (AI) is particularly suited to addressing these issues, as it provides powerful capabilities for pattern recognition in multimodal sensor data, extraction of latent correlations across spatial and temporal scales, and automated decision-making based on learned system dynamics. By learning directly from historical and real-time data, AI-driven models can reduce reliance on manually designed rules and enable adaptive, data-driven control of storage processes.

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The grain management process must consider the quality at three stages of the chain from grain intake, storage management, and dispatch[9]. **Grain intake** refers to the process of receiving and transferring grain into a granary while minimizing mechanical damage and ensuring quality during handling. **Grain storage** focuses on maintaining the grain in good condition over an extended period by controlling environmental factors and preventing spoilage, infestation, and quality degradation. **Grain dispatch** involves the controlled removal of grain from storage, ensuring it meets quality standards for subsequent transportation, processing, or distribution. Among these stages, grain intake and storage are particularly critical, as the strategies employed during these phases fundamentally determine the long-term quality and safety of stored grain. With the rapid development of Artificial Intelligence (AI) technologies in recent years, various AI-driven approaches have been applied across these stages to enhance efficiency and accuracy. For example, unsound kernel detection[10] is commonly implemented during the grain intake phase to ensure the quality of incoming grains. During grain storage, AI technologies are employed for grain pest detection and intelligent aeration control, aiming to maintain optimal storage conditions. These advancements all contribute to the ongoing development of Smart Grain Storage (SGS).

The research on SGS primarily focuses on how AI technology can be applied to address challenges in traditional grain storage methods. This review aims to summarize the key applications of AI in grain storage. While some existing SGS literature reviews[11] mainly introduce AI technologies, our primary focus is to review recent studies that explore which aspects of the grain storage process have been investigated as SGS applications. The main works of this review are as follows:

1) To provide an explicit overview of various SGS applications from four aspects: background, challenges, existing methods, and trends.

2) To provide a comparative analysis of the recent baseline models used in SGS applications from the perspective of architecture, datasets, and evaluation metric used along with model features. Comparative analysis helps researchers to get directions in future research to improve domain performance using a specific or combination of feature extractors and architectures.

3) To highlight the issues and limitations of SGS and discuss future research directions.

2 Materials and methods

2.1 AI technologies in the grain intake and storage stages

This review focuses on the application of AI technologies in the grain intake and storage stages, where AI provides the most significant support. An overview of these applications is presented in Figure 1.

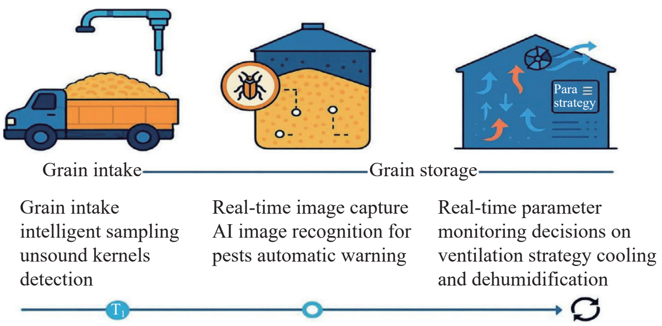

Figure 1 AI technologies applied to grain intake and storage

2.2 Structure of the survey

The rest of the article is structured as follows: Section 2 provides background information on the development of grain storage. Section 3 discusses the current AI grain storage applications from significant research, existing AI methods, and future directions. Section 4 offers a brief discussion and proposes future research directions in this area. Finally, Section 5 concludes the survey. The overall structure of the article is illustrated in Figure 2.

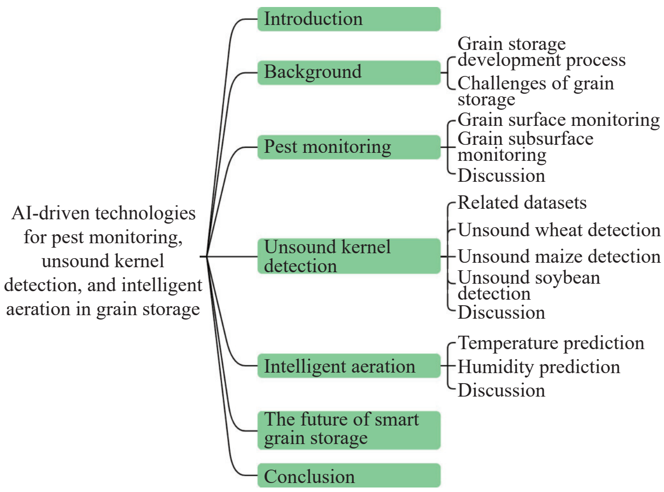

Figure 2 Structure of this review article

3 Background

3.1 Grain storage development process

The development of grain storage technology has progressed through four major stages, manual labor, mechanization, automation, and informatization, reflecting the broader evolution of industrial technology. Early grain storage relied entirely on manual monitoring and operations, resulting in low efficiency, high labor intensity, and significant safety risks. The introduction of mechanized equipment improved efficiency and reduced labor demands in processes such as grain loading, aeration, and dust removal. Subsequently, automation enabled real-time monitoring and control of key environmental parameters, integrating systems for aeration, fumigation, alarms, and grain handling to enhance safety and operational precision. With the advent of informatization, IoT- and big-data-based management platforms facilitated real-time data collection, remote monitoring, and efficient data management[12]. More recently, the integration of artificial intelligence, cloud computing, and advanced data analytics has driven the transition toward intelligent grain storage, where machine learning–based models support pest detection, grain condition analysis, unmanned inspection, risk prediction, and decision support, ultimately enabling more precise, efficient, and intelligent granary management[13].

Overall, the evolution from manual operation to mechanization, automation, and informatization has progressively improved the efficiency and reliability of grain storage management. However, these stages primarily focus on data acquisition, transmission, and basic automation, with limited capability for autonomous reasoning and adaptive decision-making. The current intelligence stage, driven by artificial intelligence technologies, represents a qualitative shift from data-centric management to model-driven understanding and control. This transition forms the technical foundation of AI-based applications in modern grain storage and motivates the systematic review of AI methodologies presented in the following sections.

3.2 Challenges of grain storage

Two key challenges in advancing grain storage into the intelligent era are: how to achieve comprehensive, all-around granary monitoring and prediction, and how to enable storage systems to implement optimal grain management strategies based on grain conditions autonomously.

The majority of grain storage losses come from biology and the environment. The deterioration of grain quality is typically triggered by the interplay among temperature, humidity, and biotic factors such as mold and insect pests. Studies have shown that high-temperature and high-humidity conditions significantly accelerate the reproduction of insects and the growth of mold, thereby increasing the risk of mycotoxin production, leading to quality degradation and economic losses in stored grain. Moreover, the processes of pest infestation and fungal infection themselves generate heat and moisture, creating localized "hot spots" that further exacerbate the deterioration. Therefore, real-time monitoring of key environmental parameters within grain bulks, such as temperature, humidity, and gas composition, as well as the prediction of their trends is essential for ensuring storage safety and enabling timely intervention when abnormalities occur.

The core storage operations conducted in granaries encompass a range of processes, including aeration and cooling to regulate grain temperature, fumigation for pest control, cleaning to eliminate foreign matter, and drying to reduce grain moisture content. Other key tasks include the formation of designated consignments, batch classification, and logistical dispatch[14]. However, these operations and strategies, such as decisions on when to fumigate, ventilate, or dry, are typically based on manual judgment. As a result, they are often subject to delays and lack precision. Therefore, it is essential to empower grain storage systems with the capability to make autonomous decisions based on real-time, site-specific conditions.

4 Applications of AI in grain storage

4.1 Stored grain insect pests monitoring

Several insect species cause significant damage to stored commodities, resulting in about 10%-20% of total storage losses. Over 600 beetle species, 70 moth species, and 355 mite species are commonly reported to cause losses in stored agricultural commodities[15]. Therefore, diagnosing insect infestation in a stored commodity is the preliminary step, as different insect species cause different types of damage. This step is vital for preventing insect population growth and for planning countermeasures and storage management strategies[16–17].

4.1.1 Grain surface monitoring

Grain surface monitoring is the most convenient and intuitive method, leveraging existing cameras installed in granaries to simultaneously capture surface images. Machine learning models are then used to detect, recognize, and count pests in the images. Finally, the results are provided to grain managers to support decision-making based on the current situation. The framework is shown in Figure 3.

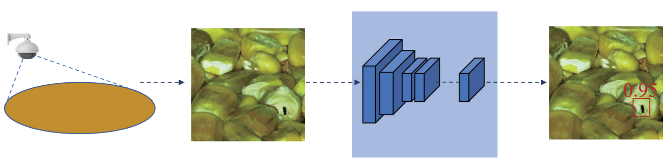

Figure 3 Grain surface pest monitoring

Existing artificial intelligence-based methods for detecting stored grain (SG) insect pests are generally studied in two scenarios: grain surface and grain subsurface. In early studies, many two-stage detection methods were predominant, such as FAST R-CNN[18], R-FCN[19] and Mask R-CNN[20]. Based on R-FCN, Shi et al.[21] proposed an improved detection network architecture for the detection and classification of eight common stored-grain insects. In their approach, DenseNet and depth separable convolution technique were integrated for feature extraction, while classification and bounding box regression were separated into different model outputs for their respective tasks. Yu et al.[22] addressed the challenges of stored-grain pest recognition and density estimation by a triple-attention convolutional network FcsNet, which integrates frequency, channel, and spatial attention mechanisms. Moreover, to acquire a high-quality dataset, this study constructed the GP10 dataset, containing 1082 images of 10 major stored-grain insect species captured in realistic storage environments. Experimental results showed that FcsNet achieves classification accuracies of 73.79% on GP10 and 98.16% on the public dataset D0.

Badgujar et al.[23] think that fine-tuning a pre-trained network using transfer learning is faster and more efficient than building and training a new network for a new task. So they fine-tuned several existing CNN models, including ResNet50, MobileNetv2, DarkNet53, and EfficientNetb0, by freezing the initial ten layers and updating the weights of the remaining layers during training. Furthermore, they argue that understanding how CNN-based models map insect features from input to prediction is crucial for the SG pest detection task, as it helps determine whether the models recognize SG pests like humans. To achieve this, they applied Gradient Weighted Class Activation Mapping (Grad-CAM) to interpret the networks during the training process, which helps to verify the network's prediction and improve network performance. Experimental results show that ResNet50 achieved the best performance, reaching an accuracy of 98.67% with a training time of only 8 min and 24 s.

With the impressive performance of the YOLO family in object recognition and classification[24], an increasing number of studies have begun developing more effective SG pest detection methods based on YOLO. Badgujar et al. created a dataset of 2,630 RGB images with 14 509 labeled stored-product insects. They trained six YOLO variants (YOLOv5s/m/l and YOLOv8s/m/l), with YOLOv8l achieving the highest performance of 77% mAP@[0.50:0.95] and real-time detection on both desktop and mobile devices. To increase the variety of SG pest species, Zhao et al.[25] constructed an SG dataset containing 3227 images of 12 SG pest species, and further enhanced YOLOv7 by introducing the Convolutional Block Attention Module and a convolutional self-attention mechanism, improving the model's ability to perceive crucial feature details. The results show that the AC-YOLO achieves a mAP@0.5 score of 91.9%. To enhance the detection performance for tiny objects, Zhu et al.[26] proposed three key improvements: (1) adding a detection layer derived from the shallow layers of the backbone to capture fine-grained features better; (2) designing an asymptotic feature pyramid module to introduce tiny object features into the neck, thereby enhancing the model's perception of SG pests; and (3) integrating a hybrid attention transformer module to improve the model's focus on small targets. Ge et al.[27] proposed the FCAYOLO model based on YOLOv8, which incorporates a feature pyramid network for multi-scale fusion, a lightweight residual module (CNeB), and an adaptive spatial feature fusion mechanism (ASFF) to enhance detection accuracy and efficiency. Experimental results show that FCA-YOLO achieves mAP0.5 of 97.29%. Sun et al.[28] present PDA-YOLO, an improved YOLOv11n-based algorithm designed for real-time detection. Addressing challenges of small target size, complex grain backgrounds, and computational efficiency, PDA-YOLO integrates three key modules—PoolFormer_C3k2 for efficient local feature extraction, Attention-based Intra-Scale Feature Interaction (AIFI) for enhanced context awareness, and Dynamic Multi-scale Aware Edge (DMAE) for precise boundary detection. Trained on a dataset of 6200 images, PDA-YOLO achieved a mAP@0.5 of 96.6%, mAP@0.5:0.95 of 60.4%, and an F1 score of 93.5%, with fast inference times (9.9 ms per image) and low computational cost.

Yu et al.[29] introduced CACNet based on VGG16 specifically for detecting small grain pests in cluttered backgrounds. Unlike traditional methods, CACNet uses a reverse cascaded feature aggregation strategy combined with Atrous convolutions to enhance multi-scale feature representation and better segment tiny pests. This study also created the GrainPest dataset, a challenging benchmark with pixel-level annotations focused on small and diverse pests amid non-salient objects. Experiments showed that CACNet achieved a structure S-measure of 91.9% and 90.9%, and a weighted F-measure of 76.4% and 91.0%, respectively. Santhanambika et al.[30] applied transfer learning with pre-trained models (VGG16, VGG19, InceptionV3, Xception) to identify pests in stored grains. VGG16 performed best with 99.8% accuracy. Based on this, a web tool using Flask and VGG16 was developed to help farmers identify pests. Tian et al.[31] introduced a unified framework PestDet for accurate and efficient detection of small stored-grain pests. Key innovations include an Enhanced Feature Extraction Block (EFEB) that enlarges the receptive field to better capture pest morphology, an one-to-many label assignment (OMLA) to balance training samples, and a normalized Gaussian Wasserstein distance (NWD) loss to improve bounding box accuracy. A Reparameterization technique speeds up inference. Tested on the GrainPest dataset, PestDet achieved better results with 90.6% mAP0.5. The related studies are summarized in Table 1.

Table 1 Grain pest detection models

Scenarios Model	Year	Base Architecture	Number of Pest Species
R-FCN+++[21]	2020	CNN	8
FcsNet[22]	2022	CNN	10
CNN-based[23]	2023	CNN	5
YOLO[24]	2023	YOLOv5, YOLOv8	6
AC-YOLO[25]	2024	YOLOv7	12
Grain surface CACNet[29]	2024	VGG16	5
YOLO-SGInsects[26]	2025	YOLOv8	5
Pre-trained Models[30]	2025	CNN(VGG16), CNN(VGG19), CNN(InceptionV3), CNN(Xception)	7
FCA-YOLO[27]	2025	YOLOv8	3
PDA-YOLO[28]	2025	YOLOv11	5
PestDet[31]	2025	CNN	6
Grain subsurface Pest Manager[33]	2024	Transformer	5
MEMS[34]	2024	CNN	3

4.1.2 Grain subsurface monitoring

To accurately assess the quantity and spatial distribution of grain pests within a grain pile, specialized pest traps are deployed to capture insects residing in the grain mass. These traps are evenly distributed. Existing methods typically use grain pest traps embedded with cameras to capture images of pests inside the grain. These images are then used to identify the number and species of pests. When a sufficient number of traps are deployed throughout the grain, the spatial distribution of pests within the grain pile can be mapped. Furthermore, various attractant lights and chemical agents are incorporated into the traps to lure and eliminate pests effectively. The framework is shown in Figure 4.

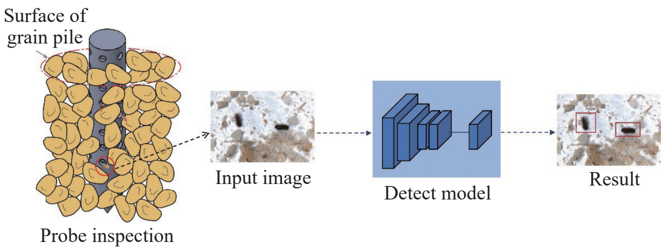

Figure 4 Grain subsurface pest monitoring

In earlier subsurface grain monitoring systems, pest probe traps were typically equipped with infrared beam sensors or photoelectric detectors to quantify the number of grain pests[32]. While these traps are effective for quantitative monitoring, they often fall short in accurately identifying pest species, usually necessitating manual examination for reliable taxonomic classification. Ma et al.[33] designed a grain probe trap and constructed a pest drop dataset—an infrared sensing signal dataset collected via infrared diodes embedded in the probe—for pest counting and species analysis. It achieved simultaneous pest counting and species identification using PestFormer, a Transformer-based multi-task model that extracts statistical features from both the time and frequency domains of input waveforms, applies dimensionality reduction, and utilizes a feed-forward network for accurate counting. To enhance species identification and mitigate device-induced variability across different sensors, a Conditional Modification Module (CMM) is incorporated. Uniquely, this work employs infrared diodes and photodiodes to detect pests, establishing a mapping between perception signals and both pest quantity and species. Experimental results demonstrate high accuracy, achieving 99.29% for pest counting and 86.97% for species identification. Balingbing[34] explores using an affordable MEMS microphone combined with a multi-layer CNN algorithm to detect and classify insect pests in stored grains based on their sound. The system recorded sounds of three major pests in stored rice and achieved an average classification accuracy of 84.51% using spectrogram features. The acoustic sensor setup, based on MEMS microphones and Raspberry Pi, offers a non-destructive, chemical-free method for early insect detection. Further improvements in noise reduction, data augmentation, and calibration are planned to enhance performance.

4.1.3 Discussion

Aligning the distribution of training data with real environmental data is important for evaluating the effectiveness of a model to address the practical grain storage issues. Most existing surface grain SG detection methods train models using idealized data, often neglect the effects of noise, illumination variability, occlusion, and high pest density encountered in real granaries. These factors can significantly degrade model performance and therefore need to be explicitly considered in algorithm design and data construction.

Although various methods have been proposed to detect grain pests by monitoring surface and subsurface of grain piles, it remains challenging to characterize the overall distribution of SG pests using a single sensing modality. Pest aggregation and migration within grain piles are strongly influenced by environmental factors such as temperature gradients, humidity levels, and gas concentrations, which cannot be directly inferred from visual observations alone. For example, image-based detection can provide spatial information about pest presence on the grain surface, while temperature and humidity probes embedded at different depths can reveal favorable micro-environmental conditions that promote subsurface pest activity. By jointly modeling these data, a fusion framework can associate visually detected pest clusters with underlying environmental patterns, enabling the inference of three-dimensional pest distribution within the grain pile.

Similarly, temporal fusion of image sequences with continuous sensor measurements allows pest population dynamics to be modeled more accurately. For instance, sudden increases in subsurface temperature or CO_2 concentration may indicate intensified biological activity before visible pest emergence on the surface. Incorporating such sensor signals into image-based detection models can support early warning and risk prediction. Multimodal approaches that integrate image and sensor data therefore provide a more stable and comprehensive representation of pest number, species, and spatial distribution, enhancing the reliability of SG pest detection systems.

The effectiveness of multimodal fusion has been demonstrated in other research fields. For example, multimodal sentiment analysis combines text, audio and video to improve emotion recognition performance[35], while multimodal object recognition integrates visible and infrared imagery to enhance object localization and shape perception under challenging conditions[36]. These studies collectively illustrate that integrating complementary modalities can substantially improve model robustness and predictive capability, supporting the adoption of multimodal strategies in SG pest distribution modeling.

4.2 Unsound kernel detection

Grain kernel detection is a critical component of quality assessment, providing essential guidance and standards for grain storage. The grain physical detection process typically involves measuring the size, weight, or density of kernels, identifying contaminants, and detecting physical signs of damage, discoloration, mold growth, or insect infestation on the kernel surface[37]. Traditionally, the identification of unsound kernels in wheat and maize has relied on manual detection, which is time-consuming and cost-inefficient. Therefore, more accurate and automated detection methods are urgently needed.

4.2.1 Related datasets

Existing machine learning-based approaches identify unsound kernels through image recognition, providing a visual means of detecting target anomalies from image data. Model training typically relies on two primary datasets (as shown in Figure 5).

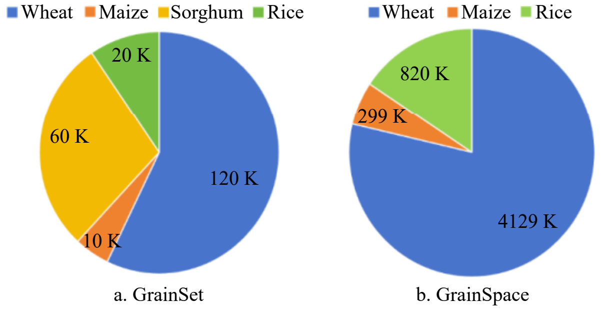

Figure 5 Unsound kernel detection datasets

GrainSet[37] is a large-scale dataset developed for the visual quality detection of grain kernels. It comprises over 350,000 single-kernel images, each annotated by domain experts. The dataset includes four types of cereal grains—wheat, maize, sorghum, and rice—collected from more than 20 regions across five countries. Each sample is accompanied by detailed metadata, including collection location and time, morphological characteristics, physical dimensions, kernel weight, and expert-labeled categories of damage and unsoundness, as determined by senior inspectors.

GrainSpace[38] is a large-scale, publicly available dataset of cereal grains, comprising approximately 5.25 million images labeled by professional inspectors. The dataset includes grain samples of wheat, maize, and rice, collected from over 30 regions across five countries.

4.2.2 Unsound wheat detection

During grain acquisition, the presence of unsound wheat kernels, such as those affected by sprouting or mold, is a critical parameter in the evaluation of wheat quality. These defects typically result from mechanical damage or microbial invasion of the embryo or endosperm, leading to a degradation in grain integrity and nutritional value. The detection of unsound kernels plays a pivotal role in wheat quality assessment, as their proportion constitutes an essential criterion in the grading and classification of wheat[39].

The related studies are summarized in Table 2. Zhang et al.[40] improved the recognition rate by fusing features extracted from VGG-16 and VGG-19 in various sequences. In detecting unsound wheat kernels, the presence of inevitably adhesive kernels poses a challenge for accurate recognition. To address this, Gao et al.[41] proposed a method that employs a segmentation algorithm to separate adhesive kernels into individual ones, followed by an improved ResNet model, combining ResNet-24 with the Convolutional Block Attention Module (CBAM) to enhance small feature detection, to detect six types of wheat kernels: sound, broken, sprouted, injured, moldy, and spotted.

Table 2 Unsound kernel detection models

Species	Model	Year	Base Architecture	Data resource	Data type
Wheat	TLFF[40]	2022	CNN(VGG-19)	self-collected	Visible light image
	Res24_D_CBAM_Atrous[41]	2022	ResNet	self-collected	Visible light image
	DCGAN[42]	2022	CNN_GAN	self-collected	Hyperspectral image
	Existing Models[43]	2022	VggNet-16, ResNet-34, EfficientNetb2, DenseNet121, Vit	self-collected	Visible light image
	Improved Mask RCNN[44]	2023	Mask RCNN	self-collected	Visible light image
	R-F-BLS	2024	Broad Learning + Pyramid Network	self-collected	Terahertz image
	MSPCNeXt[45]	2025	ConvNeXt	GrainSpace	Visible light image
Maize	Improved Mobile Vit[46]	2023	CNN+GAN	self-collected	Visible light image
	BCK-YOLOv7[47]	2023	YOLOv7	self-collected	Visible light image
	CNN-SplSpal-At[48]	2024	CNN+SS Attention	self-collected	Hyperspectral image
	VMUnet-MSADI[49]	2025	Mamba	self-collected	Visible light image
Soybean	PLS-DA[50]	2024	Partial least squares	self-collected	Hyperspectral image
	DCFFM[51]	2025	CNN+SE Attention	self-collected	Hyperspectral image

To utilize hyperspectral data for detecting unsound wheat kernels while addressing the issue of limited data, Li et al.[42] employed a data augmentation method based on DCGAN to generate additional spectral data. This approach expanded the categories with fewer samples, thereby improving the detection performance of the classifier. He et al.[43] improved existing models, including VGGNet-16, ResNet34, EfficientNet-b2, DenseNet121, and ViT, by modifying the optimizer and learning rate. The results show that the optimized EfficientNet-b2 achieved the best performance, with a precision of 99.04%. Shen et al.[44] proposed a wheat kernel segmentation algorithm based on improved Mask R-CNN to address the adhesion problem among densely distributed targets and to achieve fast, accurate, and non-destructive detection.

Jiang et al. utilized terahertz images to obtain high-resolution representations of object features and proposed a radiologist-inspired deep denoising feature pyramid network based on a broad learning system. The approach first enhances terahertz images through a deep denoising network inspired by radiological expertise. Subsequently, a feature pyramid network is applied for multi-scale feature extraction, followed by classification and recognition using a broad learning system.

To balance accuracy and efficiency, Zhang et al.[45] proposed the MSPCNeXt module, which includes two versions: MSPCNeXt-v1 and MSPCNeXt-v2. MSPCNeXt-v1 enhances feature representation by incorporating convolutional kernels of different scales to capture diverse receptive fields. It improves model accuracy and reduces computational cost by introducing 1×1 convolutions and decomposing large kernels into smaller ones. However, despite these optimizations, MSPCNeXt-v1 remains relatively complex. To further reduce convolutional complexity with minimal accuracy loss, MSPCNeXt-v2 was introduced. It achieves this by dividing the input features into multiple segments and processing them through separate convolutional channels.

4.2.3 Unsound maize detection

Maize is an important crop and industrial raw material, and advances in breeding technology have led to a rapid increase in the number of available varieties. It exhibits strong hygroscopicity and high respiration intensity. Due to its relatively high fat and nutrient content, maize is particularly prone to rancidity, provides favorable conditions for mold growth, and is highly susceptible to pest infestation. Therefore, an efficient method for detecting unsound maize is urgently needed to maintain market stability and ensure the long-term safe storage of maize.

Zhu et al.[46] proposed a corn unsound kernel detection algorithm that combines improved StyleGANv2-based sample augmentation with a lightweight MobileVit network. The approach includes constructing a dedicated image dataset and applying advanced segmentation and data synthesis techniques, ultimately achieving a recognition accuracy of 96.2% for unsound corn kernels.

Wang et al.[47] designed an image acquisition device capable of capturing high-quality corn kernel images in real time. The device operates at a frame rate of 32 FPS with an image resolution of 1024×1280, supporting timely and reliable quality detection. Furthermore, they proposed a broken maize kernel detection model, BCK-YOLOv7, which integrates a Transformer encoder block at the end of the YOLOv7 backbone to capture global contextual information. In addition, coordinate attention is introduced at multiple stages of the neck to effectively capture both channel-wise and position-sensitive features, enabling accurate detection in high-density scenarios.

To enhance the richness and precision of data representation before model training, Yang et al.[48] employ hyperspectral images as training data. As a non-destructive technology, hyperspectral imaging enables the acquisition of spectral information from both the external features and internal tissues of maize without causing damage. Moreover, it can capture subtle changes in the maize's appearance across different wave bands. Furthermore, a convolutional neural network (CNN) is integrated with spectral and spatial attention mechanisms to facilitate feature extraction and support the detection task.

Zhao et al.[49] proposed an efficient multiscale convolutional decoder, VMUnet-MSADI, for segmenting anomalous corn kernel images. This method integrates a Visual Mamba UNet with a multi-scale attention mechanism and a detail infusion decoder, aiming to improve the representational capacity and flexibility of conventional encoder-decoder frameworks. Specifically, they introduced a Multi-scale Convolutional Attention Module (MCAM) to capture salient features across multiple scales by suppressing irrelevant regions through deep convolution. Additionally, a Detail Infusion Block (DIB) was designed to enhance coarse-to-fine feature representations by incorporating both spatial and channel attention mechanisms.

4.2.4 Unsound soybean detection

Soybean is an important leguminous crop, rich in protein and oil, with substantial economic and nutritional value[50]. However, the presence of unsound soybeans can significantly degrade overall quality, reduce yield and nutritional content, and increase the risk of deterioration in surrounding soybeans when stored in the same granary. These issues pose substantial challenges to storage management and food safety across the entire soybean supply chain. Therefore, the accurate and efficient detection of unsound soybeans is critical for improving the quality, safety, and marketability of soybeans and their processed products.

Li et al.[50] applied hyperspectral imaging (HSI) in the 400-1000 nm range combined with a multi-level data fusion strategy and PLS-DA to rapidly and accurately identify four varieties of soybean seeds. By integrating both spectral and image information, the proposed method significantly improved classification performance, achieving an accuracy of 93.13% and an F1-score of 93.70%, demonstrating the effectiveness of multi-level data fusion for soybean seed variety identification.

Sun et al.[51] proposed a dual-channel feature fusion model (DCFFM) that leverages both visible and near-infrared (Vis-NIR) images and shortwave infrared (SWIR) signals. The model effectively integrates one-dimensional spectral data and two-dimensional image data to capture both spatial and spectral features of soybean samples, thereby enhancing the accuracy of unsound soybean detection.

4.2.5 Discussion

Currently, unsound grain detection methods, covering maize, wheat, and soybean, have achieved notable progress in accuracy. This progress is largely attributed to the availability of large-scale annotated datasets and advances in deep learning-based visual recognition, which have demonstrated high performance in detecting broken, moldy, insect-infested, or discolored grains.

Different imaging modalities offer unique advantages for unsound grain detection. For instance, RGB images provide clear surface information of grains; hyperspectral images reveal both surface and subsurface defects by capturing rich spectral features, though at the cost of lower spatial resolution and higher acquisition expense. Near-infrared imaging is particularly effective in identifying moisture-related and internal compositional changes, while thermal imaging excels at detecting heat anomalies caused by microbial activity or insect infestation.

However, the full potential of combining these modalities into a unified multimodal fusion model remains underexplored. The integration of complementary sensing technologies, along with the development of efficient fusion mechanisms—particularly under real-time constraints—could significantly enhance the accuracy and robustness of unsound grain detection, especially for subtle or internal defects that are invisible to conventional RGB imaging alone.

In contrast to wheat, maize, or sorghum, research on unsound paddy detection remains limited, primarily due to the inherent complexity of its processing and inspection pipeline. Detecting defects in paddy involves a multi-stage pipeline, typically including three steps: paddy, brown rice (after husk removal), and polished rice. In the first stage, the paddy morphology is assessed to determine whether the grains are physically complete. In the second stage, the appearance of brown rice is analyzed to detect mold, breakage, or insect damage through shape and color features. Finally, the polished rice is examined to assess internal integrity and quality. Each sample must go through all three stages before the batch can be deemed suitable for storage in granaries. This multi-stage workflow poses additional challenges for AI and automation, as it requires consistent defect tracking across different physical forms, repeated handling and imaging, and coordinated decision-making across stages, rather than a single end-to-end visual inspection as in other grains.

Each grain batch must pass all three stages before being deemed suitable for granary storage, which substantially increases system complexity, processing time, and deployment cost. These factors underscore the need for specialized detection methods that are explicitly designed to accommodate the multi-stage characteristics of paddy processing.

In conclusion, unsound grain detection has witnessed significant advancements in recent years, driven by the growing availability of labeled datasets and the rapid development of deep learning techniques. Various imaging modalities—such as RGB, hyperspectral, near-infrared, and thermal imaging—each offer unique and complementary perspectives for identifying different types of grain defects. While current single-modality methods already achieve high accuracy in controlled settings, their limitations in complex, real-world scenarios highlight the need for robust multimodal fusion strategies. Furthermore, specific grain types like paddy require multi-stage detection procedures, presenting additional challenges that remain under-addressed in existing research. Future efforts should focus on developing unified, cost-effective, and real-time multimodal detection frameworks to support accurate, scalable, and intelligent quality control across diverse grain types and processing stages.

4.3 Intelligent aeration

Mechanical aeration is the most widely used grain storage technology, aiming to regulate grain moisture and temperature for safe preservation. However, improper aeration can lead to inefficiency and energy waste[52]. Since grain heating is influenced by multiple factors, such as grain variety, moisture content, impurities, and pests, and storage conditions vary across ecological zones and granary types, developing an effective and tailored aeration strategy is particularly challenging and essential.

Existing intelligent aeration expert systems often struggle to generate effective aeration plans, as they typically rely on simplified models that merely follow national standards and fail to account for diverse aeration scenarios, such as temperature-reducing aeration, moisture-reducing aeration, anti-condensation aeration, heat-dissipation aeration, and conditioning aeration[53].

There has been a range of research on intelligent aeration, particularly focusing on temperature prediction and moisture prediction, both of which are key components in the advancement of intelligent aeration systems.

4.3.1 Temperature prediction

Temperature is a critical factor in determining the initiation time, method, and duration of aeration. Therefore, accurate temperature prediction can provide essential guidance for developing effective aeration strategies.

Meteorological conditions play a crucial role in influencing granary temperature. To explore the relationship between weather data and temperature, Duan et al.[54] employed multiple CNN modules and an LSTM network to extract features from meteorological and temperature data, respectively. Furthermore, to effectively capture key historical temperature patterns and reduce the impact of redundant information, they introduced a temporal attention mechanism that selectively focuses on relevant information for target sequence prediction.

To progressively capture the temporal dependencies in temperature variations, Lv et al.[55] proposed a CNN-BiGRU-Attention network for granary temperature prediction to support aeration planning. In this approach, CNN and BiGRU (Bidirectional Gated Recurrent Unit) are used to extract features and learn temporal dependencies from historical data. At the same time, an attention mechanism is employed to identify the most influential components for future temperature trends. To optimize model performance, the IPSO (Improved Particle Swarm Optimization) algorithm is utilized to efficiently search for optimal learning parameters within a short time.

To effectively learn the meteorological data, represented with sparse features, Mao et al.[56] use multiple linear regression to fuse the features. Furthermore, this approach uses the wavelet filtering to denoise the feature data for high-quality feature expression. Finally, a GRU (gated recurrent unit) model is designed to train and predict the data.

4.3.2 Humidity prediction

Humidity is also a core parameter for ensuring a favorable grain storage environment. High humidity conditions promote microorganism growth, accelerating mold and pest reproduction, which in turn further increases humidity and exacerbates grain loss[57]. Therefore, careful monitoring and regulation of humidity is an effective strategy for controlling mold and pests, and provides a basis for implementing protective measures such as enhanced aeration, air conditioning, and regular inspections to ensure food security. In particular, for long-term grain storage, accurate prediction of grain moisture is an important control measure.

To predict future humidity levels, Sindwani et al.[58] employed a RNN-based model to forecast the relative humidity of grain over the next five days at a specific temperature. Humidity variation is closely related to grain temperature and meteorological conditions. To better capture these influences, Qin et al.[59] simultaneously extracted temperature and meteorological features using a combination of CNN and LSTM, providing valuable information for predicting humidity trends. Furthermore, to represent the historical patterns of grain humidity, the study employed the Empirical Mode Decomposition (EMD) algorithm to decompose the humidity time series into multiple intrinsic mode functions (IMF) components from high to low frequencies, along with a residual component that reflects the overall trend of the original data.

4.3.3 Discussion

Although numerous studies have focused on predicting the grain storage environments to guide mechanical aeration strategies, the process remains manual. The goal of intelligent aeration is to automatically implement different aeration processes based on grain conditions, thereby maintaining an adaptive and optimal storage environment.

Aeration is a complex system influenced by various environmental factors such as geographic location, season, and other storage conditions. An intelligent aeration system must be able to adjust grain environmental conditions by applying appropriate aeration strategies. Moreover, such a system should be able to continuously self-optimize based on feedback from the effectiveness of previous aeration operations.

Based on the above analysis, there is a need for an intelligent aeration model that is initially trained on historical aeration data and then continuously self-optimized through reinforcement learning to adapt to local conditions. Specifically, the model is built upon a reinforcement learning framework, incorporating multi-source temporal encoding and a self-attention mechanism to construct a feature extraction network capable of capturing temporal dependencies and interaction patterns among various sensor inputs. The extracted representations are used as state inputs, while reinforcement learning algorithms learn an optimal policy that maps states to aeration actions. The state space includes internal and external temperature, humidity, moisture distribution, and gas concentration, whereas the action space consists of adjustable aeration parameter vectors, such as fan activation, airflow rate, and start–stop thresholds.

To make the optimization objective explicit and measurable, the reward function is designed to balance environmental regulation effectiveness and operational cost. For example, positive rewards can be assigned for reducing the average grain temperature by a predefined margin (e.g., 2°C-3°C) or lowering moisture content toward a safe target range within a given time window, while penalties are imposed for excessive energy consumption, prolonged aeration duration, or unnecessary fan switching. By jointly considering storage safety indicators and energy efficiency constraints, the reward function guides the learning policy toward achieving stable grain conditions at minimal operational cost, enabling continuous and adaptive optimization of aeration strategies.

5 The future of smart grain storage

With the advancement of AI technology, Smart Grain Storage systems are expected to operate in a manner analogous to human perception and decision-making. A wide range of sensors continuously collect heterogeneous data, including humidity, temperature, pest activity, grain moisture, and other factors. These multimodal data streams are transmitted through IoT infrastructure and jointly analyzed by an AI-based perception module, where multimodal data fusion enables the extraction of latent correlations and the formation of a unified representation of the storage state. This capability directly addresses the challenge of integrating heterogeneous sensor information that is difficult to handle using conventional rule-based methods.

In this envisioned architecture, a smart granary functions similarly to a human body, with a central control system acting as the “brain” responsible for perception, reasoning, and decision-making. This central brain, which may be implemented using a multimodal large model trained on grain storage data and domain knowledge, decomposes high-level human instructions or system-inferred objectives into a series of executable subtasks. These subtasks are then allocated to specific functional modules, such as aeration control or modified-atmosphere regulation. At the control layer, reinforcement learning enables each subsystem to learn optimal control policies from historical interactions with the storage environment, allowing adaptive responses to dynamic conditions and unexpected events without relying solely on predefined rules.

To support long-term learning and experience accumulation, an event-level knowledge graph is incorporated into the system architecture. This knowledge graph records operational actions, environmental states, outcomes, and human feedback, forming a structured representation of experiential knowledge. By continuously updating this knowledge base, the system can refine its decision-making strategies over time and improve consistency across similar storage scenarios, thereby bridging short-term control optimization with long-term knowledge evolution.

In practical operation, such a system enables intuitive human–machine interaction. For example, when an inspector queries the status of a granary, the system can summarize current environmental conditions, identify emerging risks through predictive models, and recommend targeted interventions based on learned experience. In this way, the integration of multimodal perception, reinforcement learning–based control, and knowledge graph-driven experience management provides a concrete technical foundation for the envisioned intelligent, human-like operation of future smart granaries.

6 Conclusions

Introducing intelligent methods into grain storage is crucial for improving management efficiency and preventing issues such as pest infestation, mold growth, and grain degradation. Currently, numerous studies have explored smart grain storage from various perspectives, including pest monitoring, unsound kernel detection, and environmental conditions prediction. These studies drive the development of intelligent grain storage systems. However, most existing methods primarily focus on localized perception, overlooking the importance of comprehensive inspection and autonomous decision-making. Such capabilities should encompass perception by basic models, integrated decision-making enabled by multimodal large models, fine-grained control guided by reinforcement learning strategies, and long-term knowledge storage facilitated by knowledge graphs. In the future, the development of a system capable of holistic granary inspection, along with the design and implementation of adaptive adjustment strategies, should be a key objective.

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