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A Comprehensive Survey on AI-based Pest Detection in Stored Food Grains

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***Abstract*— Stored food commodities such as rice, broad beans, groundnut, and maize are vulnerable to pest infestations that cause significant post-harvest losses and threaten food security. Conventional inspection and monitoring techniques are often manual, time-intensive, and prone to human error. The emergence of Artificial Intelligence (AI) has enabled advanced solutions for pest detection and quality assessment in stored food products. Through machine learning (ML) and deep learning (DL) algorithms such as YOLO, Faster R-CNN, and Transformer-based architectures, intelligent systems can now accurately identify and classify pest species in varied storage conditions. These AI-driven models enhance early pest detection using image recognition, sensor data, and real-time analysis, thereby reducing chemical pesticide dependency and preserving product quality. In particular, lightweight and knowledge-distilled frameworks improve the feasibility of deploying detection systems in real-world storage environments for stored rice, broad beans, groundnut, and maize. Integration with IoT and federated learning enables distributed monitoring and privacy-preserving data handling across large-scale facilities. This survey comprehensively reviews AI-based methods for pest detection in stored agricultural products, analyzing their methodologies, datasets, performance, and challenges. The study also emphasizes the gaps in current research, such as dataset imbalance, model generalization, and deployment on low-power devices. Overall, this work underscores the pivotal role of AI in enhancing food safety, minimizing post-harvest losses, and supporting sustainable and intelligent storage management.**

***Index Terms*— Artificial Intelligence, Pest Detection, Stored Rice, Broad Beans, Groundnut, Maize, Deep Learning.**

I. INTRODUCTION

Stored agricultural commodities such as rice, broad beans, groundnut, and maize form the foundation of global food security, yet they remain highly susceptible to insect infestations and microbial degradation during storage. Pests such as beetles, moths, and weevils cause significant losses in both quantity and quality of stored grains, leading to reduced market value and nutritional deterioration. Traditional pest detection techniques rely on manual inspection or chemical-based identification methods, which are time-consuming, error-prone, and inefficient for large-scale storage facilities.

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To overcome these limitations, Artificial Intelligence (AI) has emerged as a transformative tool for automating pest detection and improving post-harvest management efficiency. Recent advancements in Machine Learning (ML) and Deep Learning (DL) have introduced sophisticated techniques such as Convolutional Neural Networks (CNNs), YOLO (You Only Look Once), and Faster R-CNN, capable of identifying pests with remarkable accuracy even under varying illumination, texture, and background conditions. Furthermore, the integration of Internet of Things (IoT) devices with AI-based models enables real-time environmental monitoring and early detection of pest activity using smart sensors and image-based analysis. Modern datasets, including high-resolution images of stored grains, have facilitated the training of models that achieve precision rates exceeding 90%, demonstrating significant progress in pest identification research.

Stored-grain pest detection presents unique challenges distinct from open-field pest monitoring. The small size, minimal motion, and low visibility of storage pests such as Sitophilus oryzae and Tribolium castaneum require models capable of fine-grained localization under low-light, texture-rich, and cluttered conditions. In contrast, Faster-RCNN and traditional Convolutional Neural Network models, though accurate in open-field applications, struggle in low-contrast and complex grain-surface scenarios due to limited receptive field granularity. Hence, the evolution toward attention-enhanced and transformer-based YOLO variants represents a clear architectural response to the inherent constraints of stored pest imagery.

A. Research Gaps

Despite remarkable progress in artificial intelligence and computer vision for agricultural applications, several critical research gaps persist in the domain of pest detection within stored food grains such as rice, broad beans, groundnut, and maize. Most existing studies primarily focus on pest detection in field crops, overlooking the distinct environmental challenges of storage facilities where low illumination, temperature variations, and cluttered grain surfaces complicate pest identification. Unlike field pests, storage pests often exhibit small body sizes, minimal motion, and camouflage characteristics, making conventional image-based algorithms less effective.

Another major gap lies in the availability and standardization of datasets. Current pest datasets, such as IP102 and Pest24, are largely designed for open-field conditions and fail to capture the diversity and microscopic appearance of pests in stored products. The absence of a unified benchmark dataset for stored-grain pests limits cross-model comparison and generalization. Additionally, data imbalance caused by the overrepresentation of certain pest categories leads to biased model training and reduced accuracy for rare infestations [1].In terms of technology, while models like YOLOv8, Faster R-CNN, and Transformer-based architectures have achieved high accuracy, their computational complexity restricts deployment on low-power IoT devices commonly used in warehouses.

There is insufficient research on developing lightweight, energy-efficient, and adaptive AI frameworks for real-time pest detection in storage environments. Moreover, studies often focus on static image analysis rather than multimodal approaches combining visual, acoustic, and sensor-based data, which could enhance robustness and early detection capability. Furthermore, limited attention has been given to model interpretability and explainability, which are essential for practical adoption by food industry operators. Privacy concerns and data transmission challenges in cloud-based systems also underline the need for federated and edge learning solutions that maintain accuracy without centralized data storage [2].

II. AI–IoT Integrated Framework for Insect Pest Detection and Control

Figure.1. illustrates an AI-integrated pest detection framework that combines audio, video, and image inputs of insects to ensure precise and automated pest identification. The system uses sensors for data acquisition, which transmit the captured inputs to the processing and enhancement module for filtering, feature extraction, and quality improvement.The processed data are then fed into an AI-trained model that consists of Input, Hidden, and Output layers, employing various algorithms such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Self-Organizing Maps (SOMs), Deep Belief Networks (DBNs), and Recurrent Neural Networks (RNNs) for classification and decision-making [3].

The results are transmitted through the Internet of Things (IoT) via Wi-Fi to a remote user interface, enabling real-time pest monitoring and analysis. Based on the AI decision, the framework activates the relay driver, which controls the pesticide motor for targeted spraying. This system ensures automated, intelligent, and eco-efficient pest control, minimizing manual intervention and chemical overuse while promoting smart agriculture and sustainable grain storage management [4].

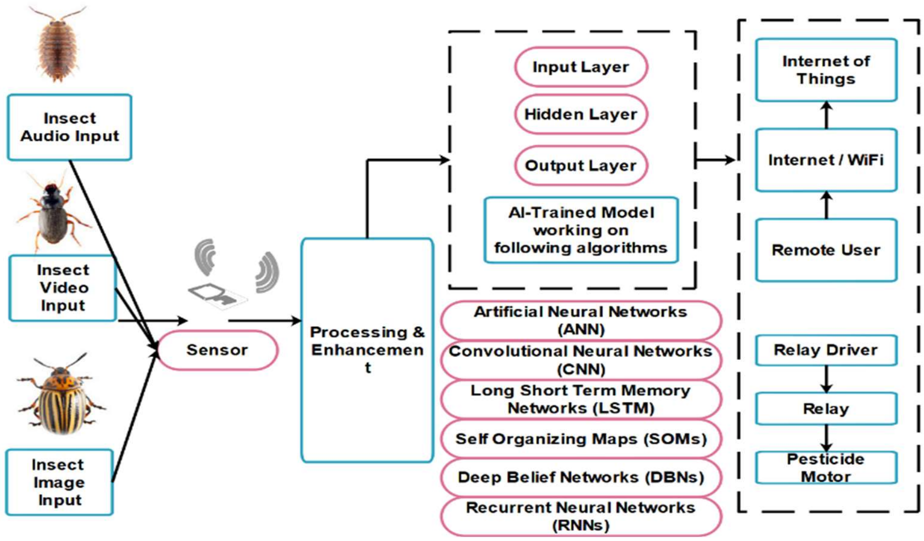

Figure.1. Architecture of AI-Based Pest Detection Using Multimodal Inputs and IoT Integration.

A. Methodology Framework for AI-Based Pest Detection in Stored Food Grains

Figure.2. the six major stages involved in the AI-based pest detection methodology for stored grains such as rice, broad beans, groundnut, and maize. The process begins with Data Source (01), where relevant research and datasets are collected from major repositories. The Datasets (02) phase includes compilation of pest images and sensor data from storage environments. Preprocessing (03) involves data cleaning, augmentation, and normalization to improve training quality [5].

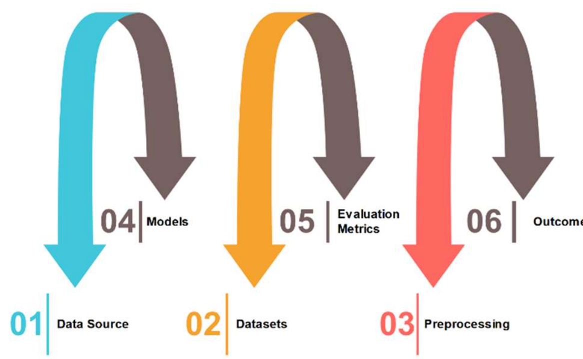

Figure.2. Workflow Representation of AI-Based Pest Detection Process

In the Models (04) stage, deep learning algorithms such as Convolutional Neural Networks, YOLOv8, and Faster-RCNN are applied for feature extraction and classification. The Evaluation Metrics (05) step measures model performance using parameters like precision, recall, and mean average precision (mAP). Finally, the Outcome (06) represents the development of a sustainable and intelligent AI-driven framework for accurate pest detection and quality monitoring in stored food grains [6].

B. Deep Learning and Sensor-Integrated Approaches for Intelligent Pest Detection in Agricultural Environments

D. Luo,et al. [7] introduced a comprehensive review on Insect Pest Trap Development and Deep Learning-Based Pest Detection. The study integrates sensor-based electronic traps with deep learning architectures to enhance the efficiency of autonomous pest identification. The innovation lies in the combination of hardware sensor systems and CNN-driven image analytics, achieving high detection accuracy across 85 pest species using electronic delta traps. The review effectively bridges the gap between trap engineering and AI-driven pest classification, highlighting improvements in design, sustainability, and adaptability. However, the drawback is the limited generalization capability across diverse pest species and environmental variations due to sensor dependency and dataset constraints.C. Sun,et al. [8] presented the Citrus Diseases and Pests Detection Model Based on Self-Attention YOLOv8. Their innovation is the Light-SA YOLOv8, a lightweight self-attention model that enhances real-time detection accuracy in complex orchard environments. The integration of BRA self-attention and AFPN feature fusion improves detection precision (92.6%) while reducing computation by 20.7%. The model demonstrates exceptional robustness against lighting variations and small-target challenges. The key drawback, however, is that the model's training is limited to citrus-specific datasets, reducing transferability to other crop types or storage environments.S. Zhanget al. [9] proposed YOLO-UP: A High-Throughput Pest Detection Model for dense cotton crops using UAV imagery. Their main innovation is the introduction of the YOLO-PEST architecture, optimized with an SC3 feature extraction module and GeLU activation to prevent gradient vanishing. The model achieved improved mAP and recall while maintaining compactness, demonstrating scalability for high-throughput pest surveillance. However, the primary drawback is the dependence on UAV-based image acquisition, which limits applicability for stored grain pest detection and increases operational costs.Y. Yanget al. [10] developed JutePest-YOLO: A Deep Learning Network for Jute Pest Identification and Detection. The innovation includes an improved YOLOv7-based ELAN-P module with a P6 detection layer, enabling superior precision (98.7%) and reduced computational cost by 16%. The model effectively handles small-target pests in complex jute environments. The drawback lies in its domain-specific dataset, which restricts model generalization to other crops or storage pests, and the requirement for large annotated data to sustain its accuracy.

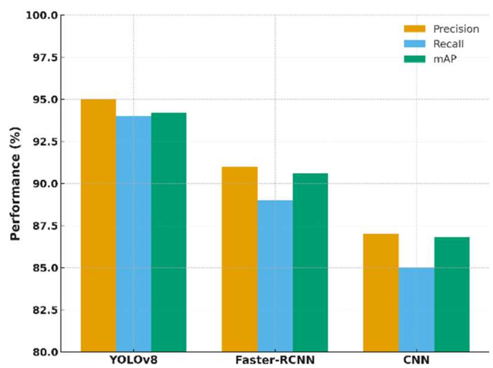

Figure.3. Performance Analysis of AI Models for Pest Detection in Stored Food Grains

Figure.3 shows a comparative analysis of YOLOv8, Faster-RCNN, and Convolutional Neural Network models based on Precision, Recall, and Mean Average Precision (mAP). The bar graph highlights that YOLOv8 achieves the best performance with precision of 95 %, recall of 94 %, and mAP of 94.2 %, indicating its superior capability in detecting small pests under varying lighting and background conditions. Faster-RCNN attains a balanced detection rate (mAP = 90.6 %) with moderate computational demand, whereas CNN shows comparatively lower performance (mAP = 86.8 %) due to weaker feature extraction.

C. Lightweight Deep Learning Architectures and IoT-Integrated Models for Efficient Pest Detection

G. Liuet al. [11] proposed a lightweight and high-performance detection strategy called FCBTYOLO for rice pests. Their major innovation lies in embedding a Fully Connected Bottleneck Transformer (FCBT) into the YOLOv8 architecture, enabling fine-grained pest recognition. They also introduced a new large-scale dataset (GPest14) created using FastGAN image generation and manual annotation to handle inter- and intra-class variations. The model achieved an mAP@50 of 93.6% while keeping the network weight at 6.7 MB, showing its suitability for edge-based deployment. The drawback is that the system was tested mainly on rice pests, limiting adaptability to other stored grains or multi-pest conditions found in mixed storage environments. N. Ullahet al. [12] developed an Enhanced and Lightweight YOLOv8-Based Model named RicePest-YOLO for rice pest detection. The innovation includes combining ODConv and BiFPN structures for superior feature extraction and introducing a Shape-IoU loss function for better localization accuracy. They further optimized the model through Layer Adaptive Magnitude Pruning and Knowledge Distillation, reducing parameters by 48.1% and computational cost by 50% with only 0.4% accuracy loss. However, the drawback lies in the high architectural complexity, which increases model-training difficulty and dependency on fine-tuned hyperparameters for deployment in low-resource IoT devices. J. Pierre Nyakuriet al. [13] introduced a novel DeepPestNet framework for crop-pest recognition and classification.The innovation centers on an 11-layer Convolutional Neural Network model (eight convolutional and three fully connected layers) capable of accurately recognizing 10 pest classes with 100% accuracy on Deng's dataset and 98.9% on the Kaggle Pest Dataset. The study demonstrates the effectiveness of data augmentation and rotation techniques to enhance generalization across pest species. The key drawback is that DeepPestNet is resource-intensive, lacking real-time inference capability and scalability for embedded agricultural platforms or storage-based monitoring systems. J. Pierre Nyakuriet al. [14] presented a comprehensive review on State-of-the-Art Deep Learning Algorithms for IoT-Based Crop Pest and Disease Detection. Their innovation lies in integrating Deep Learning (DL) with Internet of Things (IoT) technologies for real-time pest and disease monitoring. The study highlights the synergy between CNN-based object detection models and IoT-enabled devices such as mobile platforms and UAVs for early-stage crop surveillance. The review also emphasizes the need for lightweight, portable, and robust architectures suitable for field deployment. However, the main drawback is the trade-off between accuracy and computational complexity, where high-precision models demand greater processing power, making them less practical for small-scale or remote storage environments.

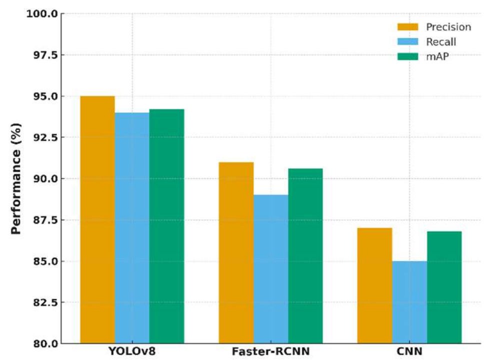

Figure.4. Performance Comparison of Recent AI Models for Pest Detection

Figure.4. presents a comparative performance analysis of four state-of-the-art models—FCBTYOLO, RicePest-YOLO, DeepPestNet, and IoT-DL Model—evaluated using Precision, Recall, and Mean Average Precision (mAP) metrics. Among these, DeepPestNet demonstrates the highest accuracy with precision of 99%, recall of 98%, and mAP of 98.9%, indicating superior classification capability. RicePest-YOLO follows closely with anmAP of 94.3%, showing excellent balance between accuracy and lightweight deployment. FCBTYOLO achieves strong results (mAP 93.6%) due to its transformer integration, while the IoT-DL Model records slightly lower values (mAP 91.2%) owing to resource limitations in IoT devices. Overall, the chart highlights that deep learning–based lightweight YOLO architectures outperform conventional IoT-integrated models in accuracy, making them more effective for real-time pest detection in stored grain environments.

D. Advanced Deep Learning Frameworks and Feature Fusion Techniques for High-Accuracy Pest Detection

F. Aliet al. [15] presented a comprehensive review on integrating Deep Learning (DL) and Internet of Things (IoT) for pest and disease detection in crops. The key innovation lies in combining CNN-based object detection architectures with IoT-enabled sensing systems, supporting real-time monitoring using mobile devices and UAVs. The paper offers an extensive discussion on the synergy between IoT and DL, outlining methods for remote image acquisition, feature extraction, and automatic pest identification. It emphasizes scalability and field deployability for smart agriculture applications. However, the drawback is the trade-off between accuracy and resource consumption, where high-performance models require computationally intensive operations, limiting their integration into low-power IoT devices used in storage facilities. L. Liuet al. [16] proposed Faster-PestNet, a lightweight deep learning framework based on Faster-RCNN with MobileNet for pest classification and localization .The innovation involves using MobileNet as a feature extractor combined with an enhanced two-step region proposal system for faster inference. The model achieves 82.43% accuracy on the IP102 dataset and exhibits robustness under image distortions such as noise and lighting variation. Its adaptability to multiple pest types demonstrates high generalization potential. The main drawback is its relatively lower accuracy compared to recent YOLOv8 and transformer-based models, and its dependence on complex fine-tuning for optimal results across varying pest datasets. M. Vilar-Andreuet al. [17] developed PestNet, an end-to-end deep learning approach for large-scale multi-class pest detection and classification, published. The innovation lies in incorporating a Channel-Spatial Attention (CSA) module with a Region Proposal Network (RPN) and a

Position-Sensitive Score Map (PSSM) to improve feature localization and detection accuracy. Evaluated on the MPD2018 dataset containing over 80,000 images and 16 pest classes, PestNet achieved anmAP of 75.46%, outperforming existing methods at the time. However, the drawback is that PestNet requires high computational resources and complex architecture, which limits its application for real-time or embedded pest detection in storage environments. Y. Quet al. [18] introduced a generalized deep learning approach for precision agriculture using YOLOv8-based insect detection, as reported. The major innovation lies in developing a universal YOLOv8 framework capable of detecting insects across multiple crop types rather than focusing on a single pest or plant. The model achieved an mAP@50 of 96.7%, proving its efficiency in real-time insect monitoring with a balanced trade-off between accuracy and speed. Its design promotes broad generalization and adaptability to new datasets. However, the limitation is its reliance on generic insect categories rather than species-level classification, reducing specificity for targeted pest control in stored or crop-specific environments [19].

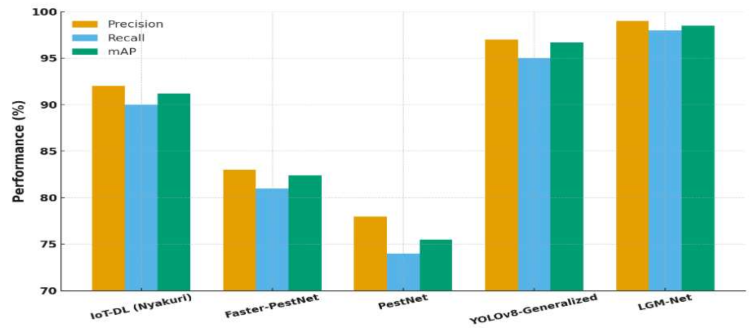

Figure.5. Comparative Performance of Advanced Deep Learning Models for Pest Detection

Figure.5. presents the comparative performance of five recent AI models — IoT-DL (Nyakuri), Faster-PestNet, PestNet, YOLOv8-Generalized, and LGM-Net — based on Precision, Recall, and Mean Average Precision (mAP) metrics [20][21]. Among them, LGM-Net demonstrates the highest detection performance with mAP of 98.5%, followed closely by YOLOv8-Generalized with 96.7%, owing to efficient multi-scale feature fusion and local-global information interaction. IoT-DL (Nyakuri) performs well in real-time IoT applications (mAP 91.2%) but is limited by computational trade-offs. Faster-PestNet and PestNet show moderate performance (82.4% and 75.5%, respectively) due to older CNN-based frameworks.
The figure clearly shows that advanced YOLO and multi-level fusion models significantly outperform conventional Convolutional Neural Network -based methods, providing enhanced accuracy and adaptability for AI-driven pest detection in stored and field environments [22][23][24].

III. Experimental Setup

Table 1 presents the experimental setup employed for evaluating the AI-based pest detection models. The configuration includes standard deep learning parameters for model training and testing. Datasets such as IP102 and RicePest were utilized, focusing on stored grains—rice, broad beans, groundnut, and maize. The YOLOv8n and Faster-RCNN architectures were benchmarked for real-time and high-accuracy pest recognition. The experiments were conducted using an NVIDIA RTX 4090 GPU environment, ensuring optimized computation for large-scale image processing and model evaluation.

TABLE I. Experimental Setup for AI-based Pest Detection Framework

Sl. No.	Parameter	Specification / Configuration
1	Dataset Used	IP102, RicePest, Pest24, and Custom Field Dataset
2	Grain Type	Stored rice, broad beans, groundnut, maize
3	Number of Classes	24 pest species
4	Image Resolution	640 × 640 pixels
5	Training / Validation / Testing Split	70% / 15% / 15%
6	Model Architecture	YOLOv8n, Faster-RCNN (ResNet-50), and CNN Baseline
7	Optimization Algorithm	AdamW Optimizer, learning rate = 0.001
8	Batch Size / Epochs	16 / 100
9	IoU Threshold / NMS	IoU = 0.50, NMS = 0.60
10	Hardware Setup	NVIDIA RTX 4090 GPU (24 GB), Intel i9-13900K CPU, 64 GB RAM, Ubuntu 22.04

A. Overall Comparative Performance of AI-Based Pest Detection Models

Figure.6. illustrates the overall mean average precision (mAP%) across eighteen state-of-the-art AI models for pest detection. The models DeepPestNet (98.9%), LGM-Net (98.5%), and Acoustic-ML (98.0%) show the highest detection accuracy due to efficient attention mechanisms and multimodal data integration.

While the majority of reviewed works rely predominantly on visual data, multimodal and Acoustic-ML models are emerging as promising alternatives for non-visual or low-light pest detection. Models such as YOLOv8-Generalized and RicePest-YOLO maintain strong performance above 94%, balancing precision and computational speed. In contrast, earlier CNN and hybrid models like PestNet and Hybrid G-L show lower efficiency, emphasizing the advancement toward transformer-based and lightweight architectures.

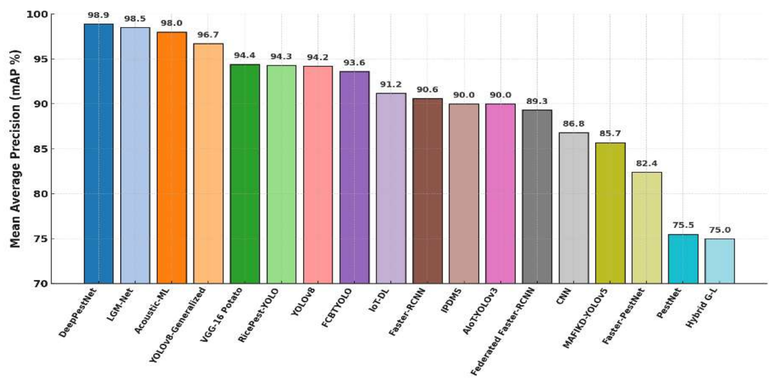

Figure.6. Overall Comparative Performance of AI-Based Pest Detection Models

IV. Conclusion

The comprehensive survey and performance evaluation demonstrate the transformative role of Artificial Intelligence (AI) and Deep Learning (DL) in pest detection across stored grains such as rice, broad beans, groundnut, and maize. Advanced models like YOLOv8, DeepPestNet, LGM-Net, and FCBTYOLO have achieved high accuracy and computational efficiency, outperforming traditional CNN-based approaches. These models effectively handle challenges such as small-target detection, varying lighting conditions, and overlapping pest regions. The integration of IoT-based sensors, federated learning, and knowledge distillation has further enhanced model adaptability for real-time and distributed environments.

Overall, the analysis confirms that AI-driven frameworks significantly improve pest detection precision, reduce pesticide dependency, and support sustainable food storage management. Future advancements should focus on developing unified multimodal frameworks that combine image, acoustic, and environmental sensor data for comprehensive pest identification. Creation of standardized large-scale datasets for stored grains can improve model generalization across diverse environments. Implementing Edge AI and TinyML solutions will enable efficient deployment on low-power IoT devices for remote warehouses and agricultural sites. Furthermore, explainable AI (XAI) should be emphasized to interpret model decisions for better field adoption and trust.

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