RESEARCH STATUS AND TREND OF GRAIN LOSS MONITORING SENSOR TECHNOLOGY
/
谷物损失监测传感器技术研究现状及趋势

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ABSTRACT
To ensure food security and reduce harvest losses, improving the monitoring accuracy of grain combine harvester operation loss is of great importance. This paper systematically analyzes the technical progress of piezoelectric sensing applications in this field. In terms of materials, piezoelectric thin films (PVDF) exhibit faster response speeds (signal attenuation shortened by 30%), but are prone to short circuits in high-humidity environments. Piezoelectric ceramics (PZT), when combined with a double-layer vibration isolation structure, can effectively reduce vibration interference errors to below 5%, providing better stability. Regarding sensor structure, the array layout enhances multi-target recognition, while the innovative double-layer cross structure enables analytical positioning of the spatial distribution of grain collisions, offering a new approach for accurately calculating loss rates. In signal processing algorithms, support vector machines (SVM) and decision trees perform well with small sample sizes; however, combining them with discrete element simulation (EDEM) is necessary to optimize feature extraction. Among these methods, the WOA-BP algorithm can control monitoring error within 6.23% through adaptive parameter adjustment. Nevertheless, current technologies still face challenges such as insufficient adaptability to varying material environments and limited algorithm generalization under complex working conditions. In the future, multidisciplinary collaborative innovation is required to develop hybrid algorithm models that integrate weather-resistant composite materials, intelligent adaptive sensor structures, and physical mechanisms, thereby establishing a high-precision, low-cost monitoring system and providing theoretical support for the research and development of grain loss detection equipment.

摘要
为保障粮食安全、减少收获环节损失，提升谷物联合收获机作业损失监测精度至关重要。本文系统分析了压电效应在该领域的技术进展：材料方面，压电薄膜（PVDF）响应速度更快（信号衰减缩短 30%），但高湿环境易短路；压电陶瓷（PZT）结合双层隔振结构则能有效降低振动干扰误差至 5%以下，稳定性更佳。传感器结构上，阵列式布局增强多目标识别，而创新的双层十字交叉结构可实现籽粒碰撞空间分布解析定位，为损失率精准计算提供新思路。信号处理算法中，支持向量机（SVM）与决策树在小样本下表现好，但需结合离散元仿真（EDEM）优化特征提取；其中 WOA-BP 算法通过自适应参数调整可将监测误差控制在 6.23%。然而，现有技术仍面临材料环境适应性不足及复杂工况下算法泛化能力有限等挑战。未来需多学科协同创新，开发耐候性复合材料、智能自适应传感器结构及融合物理机理的混合算法模型，以构建高精度、低成本监测系统，为粮食减损装备研发提供理论支撑。

INTRODUCTION
Food security stands as the paramount priority in national governance, constituting a "major national concern"*(Food and Agriculture Organization of the United Nations [FAO], 2019)*. With China's consecutive bumper harvests and sustained grain supply at historic highs, domestic production now meets consumption demands *(Chen et al., 2019)*.

However, as the world's largest food producer and consumer, China faces growing challenges in grain loss. Survey data indicates a comprehensive post-harvest loss rate of nearly 16%, primarily occurring during four stages: harvesting, transportation, drying, and storage. Notably, the harvesting phase accounts for approximately 31.25% of total post-harvest losses *(Zhan et al., 2021; Zhu et al., 2023*; *Nath et al., 2024)*. While ensuring increased grain production, urgent research is needed to enhance post-harvest loss reduction technologies, with controlling harvesting losses becoming a key focus for future conservation efforts *(Bomoi et al., 2022)*. During combine harvester operations, five types of losses occur: cleaning loss, entrainment loss, threshing loss, grain leakage loss, and cutter platform loss, where 80% results from cleaning loss and 10% from entrainment loss *(Chang et al., 2007; Nie et al., 2021; Liu et al., 2020; Zhou et al., 2010)*. Therefore, effective harvesting loss reduction can be achieved through controlling cleaning and entrainment losses *(Singh & Mehta, 2017; Zhu et al., 2025)*. Grain loss sensors can monitor cleaning and entrainment rates, enabling subsequent adjustments such as modifying the cutter platform, adjusting cutting speed, or regulating fan airflow to minimize losses *(Liu et al., 2008; Wang et al., 1999; Shi et al., 1998; Wei et al., 2023; Liu et al., 2023; Qing et al., 2024)*. In summary, grain loss sensor technology holds significant importance for ensuring food security and reducing grain waste *(Kamara et al., 2019; Yin et al., 2024)*. This paper analyzes and summarizes current developments in grain loss monitoring technologies, examining advancements in piezoelectric components, impact-sensitive plates, sensor structure research, and signal recognition algorithms to provide valuable references for future academic studies.

CLASSIFICATION AND WORKING PRINCIPLE OF GRAIN LOSS MONITORING TECHNOLOGY

Since the 1970s, international research on monitoring loss in harvesters has made significant progress. Scholars have explored various grain loss detection methods *(Chou et al., 2021)*, including photoelectric techniques *(Diekhans et al., 1990)*, acoustic-electric methods *(Liu et al., 1993; Guitersloh et al., 1990)*, and traditional piezoelectric approaches *(Barry et al., 2021)*. However, these methods remain suboptimal due to complex field working conditions and difficulties in distinguishing grains from debris. Recent advancements, however, have led to mature loss monitoring technologies based on piezoelectric effects. These innovations are now widely adopted, as piezoelectric films and ceramics are extensively used in loss sensors, coupled with continuous improvements in signal processing and algorithm optimization. Table 1 provides a classification and feature analysis of loss monitoring technologies. Although new piezoelectric methods have reached maturity, room for improvement still exists. Future research could focus on optimizing material composition and structural design of piezoelectric components to enhance stability in complex environments. Additionally, developing multimodal monitoring systems integrating other sensor technologies (such as photoelectric or acoustic-electric methods) may represent a promising direction for future development, addressing limitations of single-technology approaches.

Table 1

Classification and analysis of grain loss monitoring technology

Technological means	Monitoring methods	Technical feature
Photoelectric method	The valley flows out to block the light source, thereby showing the amount of loss	It is difficult to identify the simultaneous fall of multiple grains and to classify the grains and residues
Electroacoustic method	Using the acoustic identification technology, the acoustic signal of the soundboard is extracted to identify the amount of lost grain	Operation noise has a great influence on identification, and it is difficult to distinguish the acoustic signal between grain residues
Traditional piezoelectric method	The grain falls on the pressure sensor and generates an electrical signal, which can identify and classify the grain and the residue through different electrical signals	Traditional pressure sensors have poor resolution of grains, stems and residues, and long response time
New piezoelectric method	Based on the piezoelectric effect, the structure of piezoelectric elements and sensors and signal processing algorithm are optimized	The identification and classification of grains and residues are more accurate, the response speed is faster, and the mechanical vibration is less affected

The grain loss monitoring system employs a piezoelectric-based multi-level sensing-processing-feedback framework *(Wang et al., 2025; Xing et al., 2025)*. Its operational mechanism comprises three core components. The physical sensing layer captures mechanical vibration signals generated by grain impacts through optimized array/cross-shaped piezoelectric plates (PVDF film or PZT ceramic materials). Combined with vibration-resistant bases and precise positioning at the cleaning system outlet, it differentially detects grain signals from debris impacts. The signal processing layer converts weak piezoelectric signals into electrical signals *(Chen et al., 2024)* via charge amplification circuits. After filtering out mechanical noise through band-pass filters, temporal-frequency domain features are extracted. Machine learning algorithms establish nonlinear classification models *(Qiu et al., 2023)* to accurately distinguish between seeds and debris components like husks and stalks. The data optimization layer integrates real-time monitoring modules to calculate loss rates while synchronizing with harvester parameters (e.g., operating speed). Through feedback control, it dynamically adjusts cleaning device airflow velocity or cutter platform height to maintain loss rates within controllable ranges. This system achieves online monitoring and intelligent regulation of harvesting losses through material-structure-algorithm synergy, providing technological support for food security.

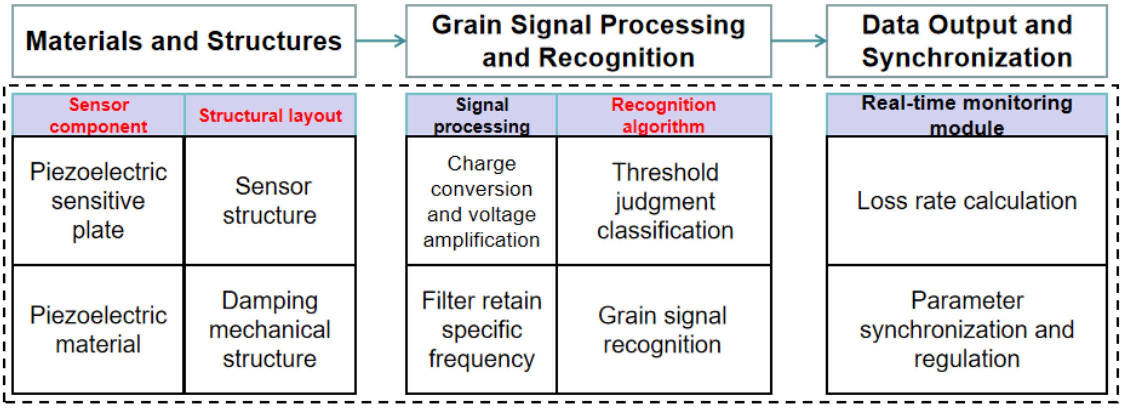

Fig. 1 – Flowchart of grain loss monitoring technology

Based on the technical principle of grain loss monitoring device, this paper selects three key aspects that affect the accuracy of loss monitoring: sensor component material, sensor structure and grain recognition signal processing algorithm for integrated analysis, and puts forward the existing problems in each aspect and the direction of optimization and improvement.

LOSS OF SENSOR MATERIALS

Piezoelectric element

Currently, piezoelectric components used for grain loss monitoring mainly include two types: piezoelectric ceramics and piezoelectric films. Piezoelectric films offer advantages such as high sensitivity, lightweight design, and flexible structure *(Huang et al., 2024)*. The piezoelectric coefficient of PVDF is 10-20 times that of traditional piezoelectric ceramics, enabling it to capture weak signals (such as single-grain impacts) with a wide response frequency range (40Hz to several kHz). Piezoelectric films exhibit faster attenuation rates than traditional ceramics, making them suitable for high-speed cleaning scenarios. PVDF films are soft and can adhere to complex surfaces while being lightweight, ideal for integration into the confined spaces of combine harvesters *(Xu et al., 1999)*. Yilmaz D *et al., (1999),* used PVDF piezoelectric films to monitor chickpea separation loss, demonstrating a correlation between monitoring accuracy and chickpea moisture content. In China, Li Junfeng and Zhou Liming also employed PVDF films as piezoelectric components in grain loss sensors, achieving monitoring errors within 5% *(Li et al., 2008; Li et al., 2009; Zhou et al., 2010)*. However, PVDF films are susceptible to interference from combine harvester vibrations and stalk debris impacts, requiring complex signal filtering. Additionally, PVDF films have environmental sensitivity defects *(Li et al., 2011)*: high temperatures may cause piezoelectric effect failure, high humidity may lead to short circuits or signal attenuation, and prolonged impact may result in fatigue fractures, limiting their stability.

Piezoelectric ceramics demonstrate exceptional piezoelectric properties, with a d33 value reaching up to 600pC/N *(Gai et al., 2025; Liu et al., 2025; Li et al., 2025)*. Their high plasticity allows customization into various shapes to meet diverse application requirements. Featuring a high Curie temperature (over 300℃ for some types), these materials maintain performance at 80℃ with only a 15% decrease *(Lu et al., 2025; Wu et* *al., 2018)*. Their cost-effectiveness makes them ideal for mass production. However, significant limitations exist: the rigid bulk material often struggles to conform to irregular surfaces, and their typical thickness of 0.5-2 mm may impair high-frequency signal capture. Additionally, their relatively low dielectric strength *(Fei et al., 2010)* causes polarization loss under strong electric fields of 75V/μm, requiring complex packaging solutions like vibration-damping rubber to suppress mechanical noise.

Table 2

Analysis and comparison of characteristics between piezoelectric film and ceramic

Application perspective	Piezoelectric film	Piezoelectric ceramics
Complex curved surface environment	Flexible design is suitable for a variety of complex scenarios	Rigid structures are difficult to fit
High temperature and humidity environment	Piezoelectric effect is prone to failure, waterproof packaging is required	High temperature resistant， waterproof packaging is required
Large scale production	Costly	Low cost
Strong electric field effect	Resistant to electric fields	Easy to depolarize

In summary, as shown in Table 2, while piezoelectric thin-film sensors demonstrate superior piezoelectric coefficients and faster response speeds, their performance remains highly sensitive to temperature and humidity fluctuations. These environmental factors can cause instability in sensor performance, leading to measurement inaccuracies. Conversely, although piezoceramic materials exhibit longer decay times, they offer greater stability and lower costs. Both material types face limitations in versatility, with current sensors primarily designed for specific crops and requiring improvements in cross-condition adaptability and interference resistance. Future research may explore novel materials with high Curie temperatures (e.g., ≥100℃), high piezoelectric coefficients, and excellent humidity resistance *(Liu et al., 2025)*, or enhance the weather resistance of PVDF films through surface modification techniques to address performance degradation issues in high-temperature and high-humidity environments.

Impact sensitive plate

Impact-sensitive plates are a critical factor affecting the monitoring speed of grain loss. When rice grains fall onto different impact-sensitive plates, the signal attenuation rates vary significantly. Moreover, the first-order natural frequency of different plate materials inversely correlates with detection speed – higher natural frequencies enable faster detection *(Zhang et al., 2019; Wang et al., 2021)*. Additionally, plate thickness impacts vibration frequency and amplitude: increased thickness enhances natural frequency and sensitivity but simultaneously reduces recognition accuracy, making it difficult to distinguish grain signals from other interference signals *(Tang et al., 2017)*. Current products primarily use 304 stainless steel or copper-clad bakelite as materials for impact-sensitive plates. Liang Zhenwei *(Li et al., 2013; Liang et al., 2018; Liang et al., 2015; Liang et al., 2014)* tested peak contact forces between three materials (stainless steel, aluminum, and brass) and rice grains, ultimately selecting 1 mm-thick 304 stainless steel plates. Liu Yangchun *(Liu et al., 2023)* conducted modal analysis of impact-sensitive plates, concluding 0.5 mm-thick 304 stainless steel was optimal. Commercialized products like those from Kais and Rayo (a leading manufacturer) typically employ copper-clad bakelite as materials for impact-sensitive plates, achieving excellent monitoring performance.

Fig. 2 – Copper-clad impact-sensitive laminate

However, existing designs exhibit significant limitations: Firstly, sensitive plate parameters (material and thickness) have not been systematically optimized for crop-specific characteristics (e.g., differences in grain hardness between rice and wheat), making it challenging to balance natural frequency with recognition accuracy.

While increased thickness enhances sensitivity, it reduces resolution and complicates the differentiation between grain signals and interference noise. Secondly, in complex operational environments (such as varying impact angles and velocities of grains), current sensitive plates are susceptible to mechanical vibrations and background noise, further compromising signal stability.

To address these issues, future innovations should focus on two key approaches:

1. Dynamic parameter optimization model: Establish a "crop-sensitive plate" matching model using machine learning to predict optimal thickness and material combinations based on historical data. For instance, Ding Li's team *(Ding et al., 2023)* utilized EDEM simulations to analyze the mechanical properties of wheat and straw impacting sensitive plates, providing theoretical foundations for parameter optimization.

2. Adaptive sensitive plate design: Develop flexible structures with adjustable stiffness or damping capabilities, such as layered composite materials (e.g., metal substrate + elastic coating) or intelligent actuation components, to accommodate diverse crops and operational scenarios.

LOSS OF SENSOR STRUCTURE

Array sensor structure

Current mature products typically employ a piezoelectric element combined with a conditioning circuit. While capable of detecting grain loss, the large sensing area makes it difficult to identify individual counts when multiple grains fall simultaneously. To address this challenge, researchers have developed array-based sensing structures by increasing the number of piezoelectric elements while reducing the required sensing area per unit. *Zhou et al., (2010),* implemented an array sensor for grain loss monitoring, with each sensor element equipped with its own dedicated signal processing circuit to prevent interference between components. As shown in Figure 3, Zhao Zhan and Ni Jun *(Zhao et al., 2013; Ni et al., 2010; Ni et al., 2015)* also designed similar sensor configurations, significantly enhancing detection accuracy during high-frequency impact testing of grains.

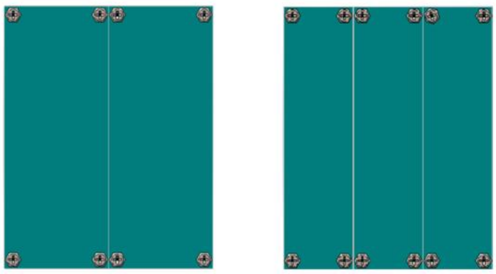

Fig. 3 – Schematic diagram of array sensor structure

Symmetrical sensor structure

In combine harvester operations, the number of grain particles at the cleaning outlet is significantly lower compared to residual debris. Without effective signal attenuation, sensors would struggle to distinguish between grain signals and interference noise. To address this, *Mao et al., (2012),* developed a symmetrical sensor structure combining two vertically aligned piezoelectric elements with identical dimensions, materials, and excitation responses. By implementing vibration compensation between the upper and lower sensors, this design enhances signal differentiation between straw debris and grain particles. While this approach effectively reduces interference, it requires precise matching of performance parameters between the piezoelectric elements, resulting in higher manufacturing complexity.

Double layer cross structure

In 2016, Bischoff *et al., (2016),* developed a sensor capable of detecting seed impact positions. This innovative design utilizes two conductive layers to identify X and Y coordinates of seeds. The concept was later implemented in China by Sun Ying and her team *(*Sun *et al., 2018)*, who named the sensor structure the "Dual-Layer Cross Structure". As shown in Figure 4, the sensor leverages the energy-conducting properties of multi-layer PVDF piezoelectric films, dividing the sensing unit into upper and lower layers: the upper layer for X-axis sensing and the lower layer for Y-axis sensing. When multiple seeds land simultaneously, the system distinguishes them through distinct XY coordinate data, achieving effective loss monitoring. The theoretical framework of this structure enhances detection accuracy, offering a novel approach for developing loss-monitoring sensor architectures.

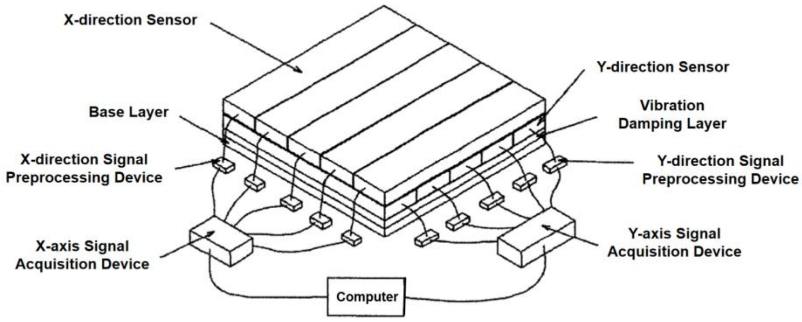

Fig. 4 –Double layer cross structure

In the design of sensor structures for grain loss monitoring, current mainstream technologies still exhibit significant shortcomings:

1. Traditional single piezoelectric element and conditioning circuit structures, while cost-effective, struggle to accurately identify the specific number of grains during simultaneous descent due to excessive sensing area, only providing rough loss trend indicators;

2. Array sensors reduce individual sensing unit size by increasing piezoelectric elements (e.g., 4×4 PVDF arrays), which enhances monitoring accuracy under high-frequency impacts but requires separate signal processing circuits for each element, resulting in complex systems, bulky designs, and increased costs. Insufficient signal isolation between elements may also cause cross-interference issues;

3. Symmetrical structures distinguish grain signals from residual noise through vibration compensation of upper/lower piezoelectric elements, significantly suppressing interference, but demand strict material, dimensional, and response characteristic matching between layers, complicating manufacturing processes and hindering mass production;

4. The dual-layer cross structure theoretically captures grain collision position information through upper/lower conductive films, breaking the bottleneck of multi-target recognition, yet relies on high-precision multi-layer PVDF film processing technology, leading to exorbitant manufacturing costs. Currently limited to laboratory simulations, it lacks reliability and durability verification under complex field environments, with unclear practical application prospects.

To address these challenges, future innovations can be pursued through multiple dimensions: for instance, developing automated calibration systems tailored to specific structures that dynamically match parameters of upper and lower piezoelectric components during production, thereby reducing process precision requirements; adopting scalable modular array designs to miniaturize sensor units while enabling flexible networking through standardized interfaces to simplify system complexity; utilizing self-isolated signal transmission technology to suppress electromagnetic interference caused by insufficient component isolation. Ultimately, this approach will create sensor solutions that combine low cost, high reliability, and strong environmental adaptability.

Seed recognition signal processing algorithm model

Grain loss monitoring sensors primarily achieve grain identification through signal processing system adjustments. The current piezoelectric sensor signal processing generally follows the classic "amplification-filtering-feature extraction" workflow. A pre-stage charge amplifier converts weak electrical signals into voltage signals, while two-stage filtering retains the characteristic frequency of grain impact *(Xu et al., 2019; Li et al., 2022)*. However, traditional methods rely on fixed thresholds for signal judgment, making them sensitive to grain types, moisture content, and installation height, requiring frequent manual calibration *(Lian et al., 2021)*. This demonstrates that simple amplification circuits cannot meet high-precision monitoring requirements under complex conditions. Therefore, researchers worldwide have proposed various algorithm models to process electrical signals from piezoelectric sensors for more accurate grain loss rate prediction *(Li et al., 2024)*. As shown in Figure 5, *Craessaerts et al., (2010),* developed a nonlinear model by measuring pressure differences and load quantities at different positions behind cleaning screens to predict grain loss rates. Meanwhile, *Hiregoudar et al., (2011),* established an artificial neural network algorithm using harvest time, width, and moisture content as input parameters, significantly improving prediction accuracy. In the same year, *Gao et al., (2011),* employed a chaotic algorithm model for grain loss monitoring. Although Duffing oscillator detection systems remain susceptible to noise, they outperform traditional time-domain detection methods in grain loss monitoring, offering a novel solution for grain recognition systems *(Yang et al., 2021)*.

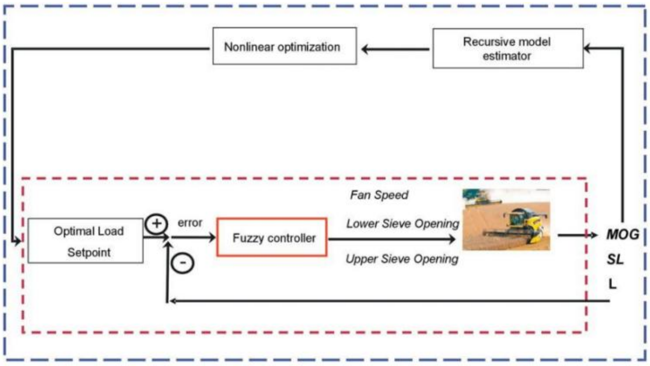

Fig. 5 – Nonlinear algorithm model

In grain loss monitoring, the limited availability of sampling equipment, monitoring conditions, and crop varieties often results in a relatively small number of usable samples, commonly referred to as "small sample scenarios". The piezoelectric sensors commonly used in grain loss monitoring operate based on nonlinear physical effects, while the data from such monitoring inherently exhibits nonlinear characteristics. Traditional linear processing methods cannot accurately reflect the true extent of grain loss, placing grain loss monitoring in a small-sample, nonlinear operational environment. Domestic research on grain recognition algorithms continues to advance. To address the complex conditions of grain identification, scholars including Cao Rui, Che Dong, Lian Yi, and Niu Caoyuan *(*Cao *et al., 2019;* Che *et al., 2019; Lian et al., 2020; Niu et al., 2023)* have developed various approaches such as majority decision, SVM (Support Vector Machine), decision trees, and WOA-BP for grain recognition. These methods aim to achieve faster response speeds, higher recognition accuracy, and broader applicability in signal identification and counting. As shown in Table 3, each algorithm demonstrates distinct advantages.

Table 3

Particle recognition effect of some algorithm models

Grain recognition algorithm model	Mean relative error of grain recognition (%)	Maximum relative error of grain recognition (%)	Monitoring period (s)
SVM	15.00	17.00	4
Decision Tree	7.28	11.82	2
WOA-BP	6.23	8.47	3

While current signal recognition and counting algorithm models have demonstrated promising results, they still face multiple limitations.

1. Insufficient sample size and generalization capability: Existing algorithms (e.g., SVM, decision trees) primarily rely on limited laboratory or specific operational samples, making them inadequate for diverse field environments such as straw occlusion, grain aggregation, and varying collision angles. For instance, SVM maintains stability with small datasets but shows sensitivity to noise and struggles to effectively model nonlinear distortions in piezoelectric signals (e.g., amplitude fluctuations caused by different collision angles).

2. Inadequate nonlinear feature modeling: Piezoelectric sensor signals are inherently nonlinear dynamic systems. However, traditional linear algorithms depend on manual feature engineering, failing to capture higher-order nonlinear correlations. For example, the nonlinear characteristics of contact force variation curves during wheat grain-stubble impact on sensitive plates remain underutilized.

3. Insufficient dynamic adaptability: Although existing models possess strong search capabilities, their high parameter sensitivity makes them ill-suited for dynamic conditions like feeding rates and grass-to-hull ratio variations in combine harvesters. EDEM simulations reveal that wheat grain recognition accuracy reaches 98.4% at 300 mm height, but actual field height fluctuations may amplify errors.

Based on these findings, this paper proposes feasible algorithmic innovation directions for reference.

1. Multi-source algorithm fusion enhances model adaptability: By integrating chaotic algorithm preprocessing with deep learning classification, this hybrid model leverages the chaotic algorithm's strong sensitivity to nonlinear signals under small sample conditions and deep learning's autonomous feature

extraction capabilities, achieving robustness in dynamic operating environments while maintaining deep feature modeling depth.

2. Transfer learning strengthens generalization: Utilizing collision mechanics data generated by Discrete Element Method (DEM) or Finite Element Method (FEM) simulations combined with limited field measurement data for transfer learning effectively mitigates small-sample limitations. For instance, Liu Xiaohang's team demonstrated the feasibility of their transfer learning-based corn kernel detection model maintaining high accuracy even in occlusion scenarios.

3. Deep integration of physical mechanisms and data-driven approaches: Establishing nonlinear dynamic models based on piezoelectric collision mechanics combined with machine learning for non-stationary signal modeling overcomes limitations of traditional linear feature engineering.

4. Reinforcement learning dynamically adapts to operational fluctuations: Introducing reinforcement learning to adjust model parameters online addresses dynamic parameter variations in combine harvester operations, while compensating for single-sensor limitations through multi-sensor data fusion (light, acoustic, and pressure signals), thereby enhancing model stability under complex operating conditions.

PROBLEMS AND PROSPECTS OF GRAIN LOSS MONITORING TECHNOLOGY

Exploration and composites of piezoelectric element materials

Piezoelectric components in grain loss monitoring face limitations including environmental adaptability and material constraints. PVDF films are susceptible to interference from high humidity and mechanical vibrations. While piezoelectric ceramics exhibit superior stability, they demonstrate slower response speeds and require complex packaging processes *(Mangi et al., 2025)*. Innovation in piezoelectric materials should focus on multidimensional breakthroughs: Composite sensing technology that combines advantages of piezoelectric and piezoresistive materials *(Nauman, 2021)*, enhancing signal acquisition efficiency through array-based layouts while reducing noise interference; and development of novel materials with high Curie temperatures (e.g., ≥100℃) and humidity-resistant piezoelectric properties to overcome existing material performance bottlenecks *(Fang et al., 2025; Zhao et al., 2025)*.

Impact sensitive plate research and development and model construction

The impact-sensitive plate in grain loss monitoring faces three core challenges: Current material and thickness parameters for sensitive plates have not been systematically optimized for crop-specific characteristics (e.g., differences in grain hardness between rice and wheat), making it difficult to balance natural frequency with recognition accuracy *(Liang et al., 2015)*. While increased thickness enhances sensitivity, it reduces resolution and complicates the differentiation between grain signals and interference noise *(Ni et al., 2015)*. Moreover, in complex operational environments, existing sensitive plates are susceptible to mechanical vibrations and background noise, further compromising signal stability *(Rossi et al., 2023)*. To address these issues, future innovation directions include: establishing crop-sensitive plate parameter matching models for dynamic optimization *(Chen et al., 2024)*; developing adaptive sensitive plates that adjust stiffness or damping characteristics dynamically to adapt to diverse crops and operational conditions, thereby enhancing monitoring robustness *(Du et al., 2025)*.

Innovations in the structure of loss monitoring sensors

In the structural design of grain loss monitoring sensors, current mainstream technologies face the following core challenges: traditional single-piezoelectric structures have large sensing areas but low accuracy for multi-grain recognition; array configurations improve precision but increase complexity and costs due to multi-circuit integration *(Qu et al., 2024)*; symmetrical structures require strict performance matching between upper and lower piezoelectric elements, making mass production difficult; double-layer cross-structured designs rely on precision multilayer film processing, which is costly and lacks field validation *(Sun et al., 2017)*. To address these issues, future solutions could adopt modular array designs combined with flexible circuit board technology to enhance signal integration and reduce hardware redundancy *(Ullah et al., 2024; Yan et al., 2024)*; optimize manufacturing parameters through finite element simulations (e.g., grain collision dynamics modeling and structural stress analysis); simplify multi-layer structure fabrication by introducing 3D printing technology *(Yuan et al., 2023; Wolstrup et al., 2025)*; establish standardized testing platforms based on real-field operations to systematically verify environmental adaptability and stability of new sensors, thereby accelerating industrialization *(Wolstrup et al., 2025; Yan et al., 2024)*.

Fusion and coordination of grain signal recognition algorithm

In the field of grain kernel signal recognition, selecting small sample and nonlinear algorithm models as solutions can yield good results. However, due to limitations such as algorithmic constraints, instability, overfitting, and parameter sensitivity, no single model can perfectly adapt to the specific scenario of grain loss monitoring. The core challenge for current algorithms lies in the dual constraints of small samples and nonlinearity, necessitating innovation through deep integration of physical mechanism modeling and data-driven learning *(Castillo-Girones et al., 2025)*. Future researchers could combine multi-source algorithms (e.g., chaotic algorithm preprocessing + deep learning classification), adopt transfer learning techniques to leverage existing datasets for enhanced generalization capabilities in complex field operations *(Hossen et al., 2025)*, and utilize interdisciplinary approaches with hardware co-design to overcome limitations of single algorithms, achieving high-precision adaptive monitoring under complex conditions *(El Sakka et al., 2025)*. With the deep integration of digital technologies and agricultural equipment, grain loss monitoring technology will inevitably advance toward higher precision, stronger robustness, and lower costs. Through interdisciplinary innovations spanning materials science, information science, and agronomy, this field will provide solid technical support for China's implementation of the "Grain Storage in Technology" strategy and food security assurance.

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