A REVIEW OF INNOVATIVE DESIGN AND INTELLIGENT TECHNOLOGY APPLICATIONS OF THRESHING DEVICES IN COMBINE HARVESTERS FOR STAPLE CROPS

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主粮作物联合收获机脱粒装置的创新设计与智能化技术应用研究综述

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ABSTRACT

This paper reviews the progress in innovative design and intelligent technology applications of threshing devices in combine harvesters for staple crops. To address the issues of poor adaptability and low intelligence in traditional threshing systems, researchers have significantly improved threshing performance by optimizing threshing components and drum structures. Meanwhile, machine vision and deep learning have achieved important breakthroughs in feed rate monitoring, breakage and impurity rate detection, and intelligent control. This review aims to provide a reference for research and applications in threshing system structural optimization and operational parameter control.

摘要

本文综述了主粮作物联合收获机脱粒装置的创新设计与智能化技术应用进展。针对传统脱粒装置适应性差和智能化程度低的问题，研究者通过优化脱粒元件和滚筒结构显著提升了脱粒性能。同时，机器视觉和深度学习在进料速度监测、破碎率与含杂率检测及智能控制方面取得了重要突破。综述旨在为脱粒系统结构优化、作业参数控制等研究与应用提供参考

INTRODUCTION

With the rapid growth of the population and the increasing demand for food, food security plays a crucial role in economic and social development. Achieving efficient and low-loss mechanized harvesting is a key approach to increasing grain yield *(Shahbazi et al., 2025)*. The combine harvester is a large-scale harvesting machine that integrates multiple functions *(Fu et al., 2018; Ni et al., 2021; Yin et al., 2024)*, including cutting, threshing, and cleaning. While ensuring operator comfort *(Marin et al., 2024; Vlăduț et al., 2023),* the performance of the threshing system directly determines the quality and efficiency of grain crop harvesting. With the gradual application of emerging technologies such as sensor technology and automatic control in agricultural machinery for navigation *(Xie et al., 2023; Yao et al., 2024)*, path planning *(Chen et al., 2024),* and operation quality monitoring *(Guo et al., 2025)*, there is significant potential for the innovative design and intelligent upgrading of combine harvester threshing devices. These advancements lay the foundation for achieving clean, low-loss, and highly efficient intelligent harvesting with combine harvesters *(Mandal et al., 2024)*.

The threshing system of a combine harvester primarily consists of a threshing drum, concave, transmission, and adjustment mechanisms *(Miu et al., 2008b, 2008a)*. By adjusting operational parameters such as drum speed and feed rate, optimal threshing quality can be achieved *(Vlăduț et al., 2023)*. Based on the different conveying directions of crops within the drum, various structural forms of threshing devices have been developed, including tangential threshing devices *(Hussain et al., 2024)*, axial threshing devices *(Srison et al., 2016; Vlăduț et al., 2022)*, and hybrid tangential-axial threshing devices *(Chai et al., 2020)*.

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Currently, threshing systems meet the requirements for harvesting various staple crops; however, challenges remain, including high grain breakage rates, high impurity and loss rates, and a lack of precise control *(Guo et al., 2019).* In particular, under challenging harvesting conditions such as high humidity, threshing devices are prone to clogging and entanglement *(Tang et al., 2019).* In terms of operational parameter and quality monitoring, installing quality detection sensors on key working components *(Liu et al., 2025)* has enabled the monitoring of breakage rates and loss rates *(Chen et al., 2024)*.

However, due to environmental interferences such as vibration, dust, high humidity, and high temperatures, sensors often suffer from low real-time performance, stability, and accuracy *(Li et al., 2024; Liu et al., 2024)*. Additionally, the lack of standardized communication protocols among various sensors and actuators leads to difficulties in integrating, sharing, and monitoring multi-source heterogeneous data *(Qiu et al., 2022)*. Furthermore, although machine learning- and deep learning-based operation quality detection methods *(Hasan et al., 2023)* have achieved significant advancements, challenges remain in acquiring large-scale datasets, manual data annotation, and the high cost of training data *(Ahmed et al., 2025).*

In terms of intelligent control strategies and algorithms, a state-space model of the threshing system has been established, and expert systems based on empirical rules have been integrated into the control module *(Omid et al., 2010)*. Additionally, associative models such as neural networks have been introduced to capture nonlinear relationships, while methods like fuzzy control *(Craessaerts et al., 2010)* and adaptive regulation strategies *(Zhu et al., 2025)* have been employed to achieve dynamic adjustment of operational parameters. However, due to limitations in sensor detection accuracy, the generalizability of algorithm models, and insufficient machine-wide coordination, modeling the complex, dynamic, and nonlinear relationships between operational parameters and crop attributes over time remains challenging. As a result, real-time responsiveness is poor, and the threshing control system lacks deep adaptive capabilities and multi-parameter decoupling *(Zhang et al., 2022a)*.

In summary, due to the variations in planting patterns and harvesting environments of different staple crops, existing data acquisition and information fusion methods still face challenges related to models and algorithms in practical applications. These issues significantly hinder the real-time control capability of threshing systems in adjusting operational parameters. Given this context, this study systematically reviews recent research progress in the structural design, operational performance optimization, and integration of intelligent technologies in combine harvester threshing devices for staple crops. Furthermore, potential future research directions and development trends are explored to provide insights and references for the continuous innovation and practical application of threshing devices.

INNOVATIVE DESIGN OF THRESHING DEVICE STRUCTURE

The primary operating targets of staple crop combine harvesters include maize, soybeans, and cereals (wheat and rice), necessitating the design of threshing devices tailored to the specific properties of different crops. Therefore, in the structural innovation of threshing devices, key operational components should be interchangeable and adjustable to accommodate various crop characteristics. Additionally, the combined application of multiple threshing structures, the flexibility of critical components, and lightweight design are fundamental principles in the innovative structural design of threshing devices *(Dong et al., 2023; Zhao et al., 2023)*.

Corn Threshing Devices

For maize crops, the maize ear has a large volume, hard kernels, high adhesion strength between kernels and the cob, and a high moisture content. Therefore, maize grain harvesting requires a threshing system with sufficient throughput and high processing efficiency. To ensure low breakage while maintaining effective threshing, high-intensity impact or rubbing mechanisms are commonly employed *(Qian et al., 2017; Steponavičius et al., 2023)*. By adjusting the threshing drum diameter, various variable-diameter and variable-speed threshing drum designs have been developed. For instance, *Wang et al., (2021),* designed a conical variable-diameter threshing drum (Figure1), which enhances the ear-holding capacity in the threshing section, loosens the interaction forces between kernels and between kernels and the cob, and enables efficient threshing and conveying of maize ears with different diameters.

Traditional concaves in maize combine harvesters are typically designed with a fixed radius and are mostly rectangular or arcuate in shape, making it difficult to meet the diverse harvesting requirements of different crops and moisture levels. To address this limitation, *Pužauskas et al., (2017),* proposed the concept of "inclined beam and variable-radius concaves" and found that when the working surface of the inclined beam was set at 45°, maize kernel separation efficiency, breakage rate, and threshing losses were optimized. By innovating the operational mechanism of threshing drums and the structural design of threshing components, *Hou et al., (2023),* developed a novel low-damage, high-efficiency threshing drum. Additionally, *Tang et al., (2024),* designed a low-loss threshing device equipped with a "rotatable concave sieve" (Figure 2), in which the concave rotates in the opposite direction to the drum, significantly increasing the residence time of maize ears in the threshing space. The concave is designed as an adjustable structure, enabling high threshing efficiency without the need for a substantial increase in drum speed, while simultaneously reducing mechanical damage to the kernels.

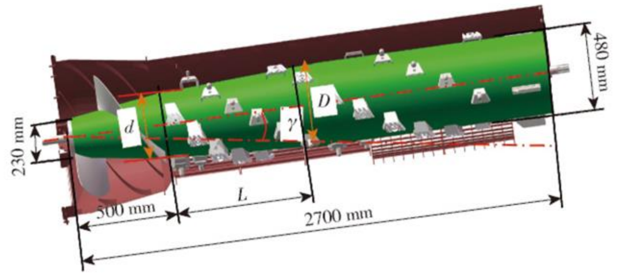


Fig. 1 - Variable diameter threshing drums
(Wang et al., 2021)

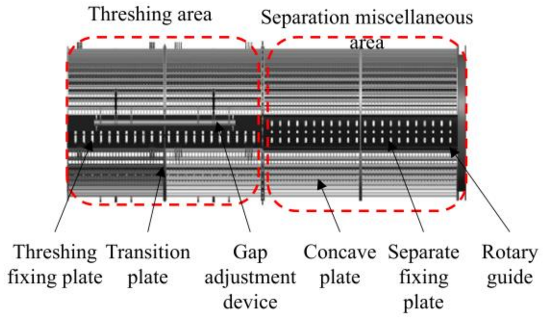


Fig. 2 - Schematic of rotary concave screen
(Tang et al., 2024)

Traditional threshing devices typically employ rigid spike-tooth or short rasp-bar threshing elements, which often result in either "high impact and high breakage" or "insufficient threshing." Consequently, the concept of flexible threshing elements has been introduced. For instance, *Li et al., (2020),* found that rubber composite spike-tooth elements significantly improved the threshing performance of high-moisture maize ears. Similarly, *Chen et al., (2020),* demonstrated that a combination of "flexible spike-tooth and dual-torsion spring-loaded short rasp bars" effectively reduced impact damage to kernels. Building on these findings, *Song et al., (2022),* proposed a flexible threshing device featuring "front-end flexible spike-tooth elements and rear-end elastic short rasp bars with pressure springs" (Figure 3). This design balances maize ear grasping, helical conveying at the front end, and flexible impact and rubbing-based threshing at the rear end, thereby minimizing kernel damage.

For high-moisture maize threshing, *Li et al., (2023),* introduced a flexible threshing element composed of variable-stiffness conical springs and impact tooth bars, which can appropriately rebound or yield upon contact with maize ears. Similarly, *Li et al., (2023),* designed a novel threshing drum incorporating a combination of rasp bars, separation rods, and impurity-removal bars. Compared to conventional spike-tooth drums, the increased contact area between the rasp bars and kernels reduces impact and clamping-induced breakage, particularly under high-moisture conditions.

Additionally, *Gong et al., (2024),* drew inspiration from torsion spring structures to develop a variable-stiffness maize flexible threshing element composed of conical springs and short rasp bars. Furthermore, *Xing et al., (2024),* designed a threshing element with helically arranged rasp-bar blocks installed in the threshing section (Figure 4). The improvements in threshing elements mainly focus on the alternating arrangement of different threshing components or the adoption of novel flexible threshing elements to minimize maize kernel breakage.

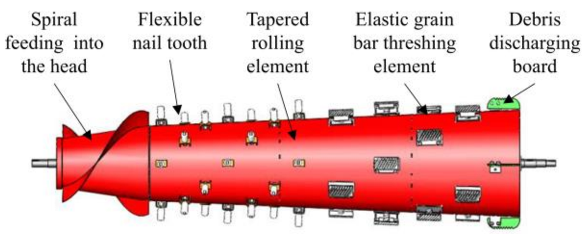


Fig. 3 - Flexible nail tooth and elastic grain bar threshing drum *(Song et al., 2022)*

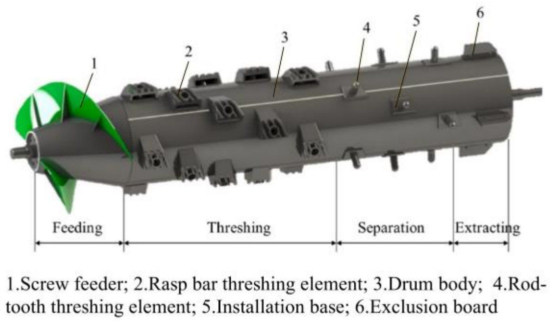


Fig. 4 - Spirally arranged rasp bar threshing elements *(Xing et al., 2024)*

In summary, through concave adjustment, flexible improvements in threshing elements, and optimization of variable-diameter drum structures in maize threshing devices, the contradiction between incomplete threshing and high kernel breakage rates can be effectively mitigated. These advancements enhance the adaptability of threshing devices to varying feed rates and moisture conditions, thereby improving overall threshing efficiency and grain quality.

Grain threshing devices

For cereal threshing, the adhesion force between the grain and the husk (or pod) is relatively low, the grain size is small, and the moisture content is lower. Additionally, cereal crop stems are relatively thin and brittle. As a result, threshing elements in cereal harvesters predominantly utilize arc-tooth and spike-tooth structures to achieve threshing through friction and rubbing *(Abdeen et al., 2021; Hu et al., 2024)*. For example, the application of a rigid-flexible coupled arc-tooth design has been shown to reduce stem clogging and decrease grain breakage rates.

For concave adjustment, the perforation design must ensure high screening efficiency, typically utilizing hydraulic or electronically controlled adjustment mechanisms *(Su et al., 2020)*. For instance, *Yuan et al., (2024),* adopted a rod-tooth threshing drum (Figure 5) combined with an adjustable concave clearance design, demonstrating excellent adaptability to uneven wheat feeding and moist crops.

Based on the segmented axial-flow threshing and separation device for rice and wheat, *Kang et al., (2022),* designed a symmetrically adjustable concave, allowing for dual-sided threshing gap adjustments to enhance threshing performance across varying moisture conditions. Furthermore, *Kang et al., (2025),* developed an independently adjustable concave system comprising long concave sieves, short concave sieves, electric cylinders, and a control system. This system modifies the internal rubbing intensity of the material, thereby improving threshing efficiency.

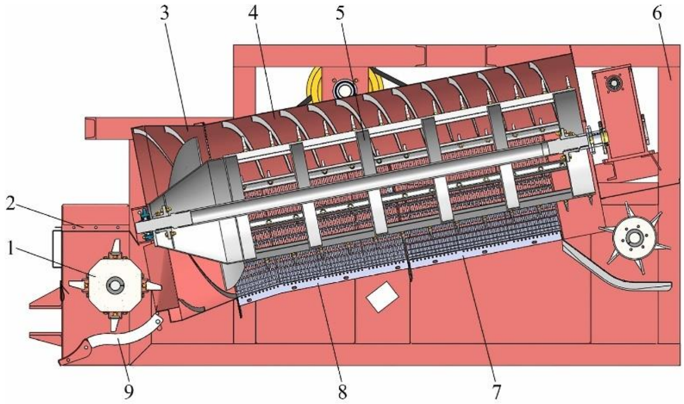


Fig. 5 - Tangential and longitudinal-axial threshing and separating unit *(Yuan et al., 2024)*

1. Tangential drum; 2. Tangential cover; 3. Conical cylinder; 4. Longitudinal axial cover; 5. Axial-flow drum; 6. Frame; 7. Rear axial concave; 8. Front axial concave; 9. Tangential concave

For the optimization of threshing drum structures, the primary approach involves using variable-diameter and variable-speed threshing drums to address the adaptability limitations of fixed-diameter drums in the threshing and separation zones. Typically, the threshing zone adopts a larger diameter, while the separation zone utilizes a smaller diameter conical drum. For instance, *Abdeen et al., (2025),* evaluated and optimized the performance of a longitudinal axial-flow threshing device using a conical threshing drum. Similarly, *Zhang et al., (2022b),* designed an axial threshing and separation device incorporating a front-end rasp bar and a rear-end spike-tooth structure, demonstrating that the combination of rasp bars and spike teeth meets the operational requirements for both threshing and separation.

Additionally, differential-speed threshing drums can be designed to enhance crop feed rate adaptability. Examples include a segmented threshing drum with an adjustable rotational speed difference between the front and rear sections *(Kang et al., 2023)* (Figure 6) and a coaxial differential-speed threshing drum with a spiral plate-tooth axial threshing system *(Zhou et al., 2022)*. Furthermore, *Wang et al., (2022),* developed a combination threshing device with independently rotating inner and outer drums, effectively reducing grain breakage during threshing. For rice threshing, *Liu et al., (2022), Wang et al., (2023),* designed a variable-diameter rice threshing drum (Figure 7), which improves adaptability to varying feed rates and effectively reduces stem clogging issues.

In summary, the innovative design of cereal threshing devices enhances crop throughput capacity through concave adjustments, reduces grain breakage by incorporating flexible threshing elements, and improves multi-crop adaptability with variable-diameter and variable-speed drum designs. These advancements provide a critical foundation for enhancing the threshing performance and intelligent control of combine harvesters, offering significant engineering application value.

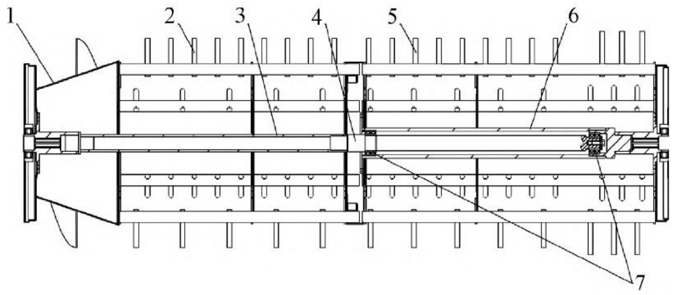
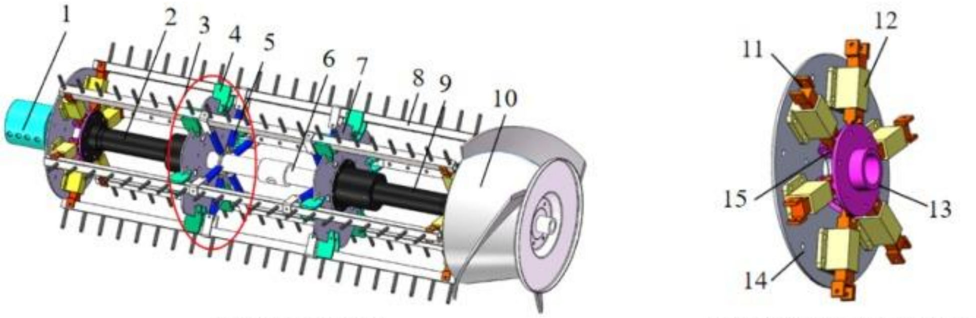


Fig. 6 - Structure diagram of differential threshing cylinder *(Kang et al., 2023)*
1.Feeding auger; 2. Front threshing cylinder; 3. Low speed hollow shaft; 4. Low speed solid shaft; 5. Latter threshing cylinder; 6. High speed hollow shaft; 7. Bearing



a. Overall structure b. Side adjustment mechanism

Fig. 7 - Schematic diagram of the variable-diameter threshing drum
(Liu et al., 2022; Wang et al., 2023)
1. Hydraulic rotary joint; 2. End hollow hydraulic cylinder; 3. Middle adjustment mechanism; 4. Baffle; 5. Tension spring; 6. Main shaft; 7. Middle support plate; 8. Threshing rod; 9. Feeding side hollow hydraulic cylinder; 10. Feeding wheel; 11. Connecting rod; 12. Sliding groove; 13. Guide rail push plate; 14. Side support plate; 15. Pin shaft.

INTELLIGENT TECHNOLOGY FOR THRESHING SYSTEMS

The primary objective of the intelligent technology applied to threshing and separation in combine harvesters is to enhance threshing efficiency, reduce loss and breakage rates, and ensure optimal operational quality across different crops and field conditions. This paper reviews research progress in key areas, including feed rate detection, breakage and impurity content monitoring, entrainment loss detection, and intelligent control. It explores the application of machine vision technology, deep learning models, and intelligent optimization algorithms in threshing systems, providing a reference for the integration of intelligent perception, decision-making, and control in threshing system operations.

Intelligent feed rate detection

In traditional combine harvesters, the grain feed rate is typically estimated based on the forward speed and cutting width, which results in low accuracy since the feed rate is influenced by multiple factors, including crop density, header height, cutting width, grain moisture content, and forward speed *(Zhang et al., 2018)*. In recent years, with the application of sensor technology and deep learning in data detection, significant advancements have been made in grain feed rate detection technology. Furthermore, multi-sensor data fusion techniques have further improved detection accuracy.

Mechanical sensor detection technology

Mechanical sensor detection technology estimates the feed rate based on pressure variations as grain material passes through the auger, feeder house, and threshing drum. Typically, pressure sensors are installed on the feeder house bottom plate, while torque sensors are mounted on the auger drive shaft, concave, and drum bearings to measure pressure and torque fluctuations during harvesting. By integrating these measurements with the power consumption and operating speed of the threshing system, the feed rate can be calculated.

For instance, *Liang et al., (2013),* developed an online monitoring system for feed rate estimation based on drum torque, rotational speed, grain flow, and the straw-to-grain ratio. However, the system exhibited a certain degree of data latency. To investigate the relationship between feed rate and header torque, *Zhang Z. et al., (2019),* designed a feed rate monitoring system based on the torque of the header drive shaft, revealing a strong correlation between header torque and feed rate. *Abdeen et al., (2022),* constructed a longitudinal axial-flow rice threshing platform and designed a threshing drum cover stress monitoring system using force-sensitive resistors. Their results showed that the force signals collected by the thin-film sensors were significantly correlated with drum rotational speed and feed rate. Additionally, by installing vibration acceleration sensors at the bottom of the inclined conveyor (Figure 8), *Liang et al., (2024),* investigated the impact of feed rate on the vibration characteristics of the combine harvester's inclined conveyor.

Fig. 8 - Installation positions of the vibration acceleration sensor *(Abdeen et al., 2022)*
(a) Position of the inclined conveyor in the combine harvester; (b) Sensor placement on the inclined conveyor

With the advancement of multi-sensor fusion technology, the integration of multiple parameters—such as header torque, inclined conveyor torque, and crop properties—has significantly improved the accuracy of feed rate detection. *Zhang et al., (2022),* proposed a feed rate detection method based on multi-sensor decision-level fusion (Figure 9) and developed a feed rate monitoring system for grain combine harvesters. Their study analyzed the correlation between operating speed, crop density, auger torque, conveyor torque, and cylinder torque with feed rate. The results demonstrated that the proposed detection system exhibited high monitoring accuracy and stability.

To further enhance detection precision, *Sun et al., (2022),* developed a neural network-based feed rate detection method by incorporating multiple parameters, including header drive shaft torque, header height, and grain moisture content. Among these approaches, torque and pressure measurements provide more direct and precise assessments. However, due to the distance between measurement points and the header, these methods exhibit a certain degree of data latency.

To address this issue, a feed rate monitoring system based on the reel force at the header position was developed (Figure 10). This system utilizes force sensors and angle sensors to detect variations in forward speed, reel rotational speed, header height, and plant bending force, enabling an accurate estimation of the combine harvester's feed rate *(Chen et al., 2025)*.

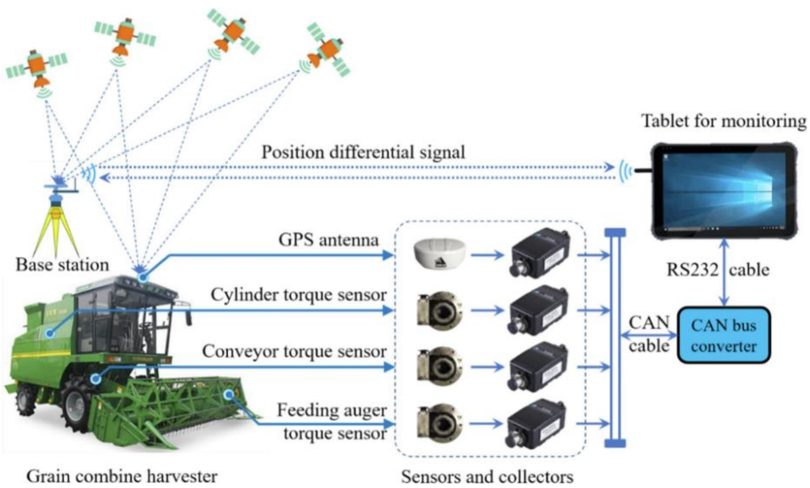


Fig. 9 - Multi-sensor fusion-based crop feed rate detection method *(Zhang et al., 2022)*

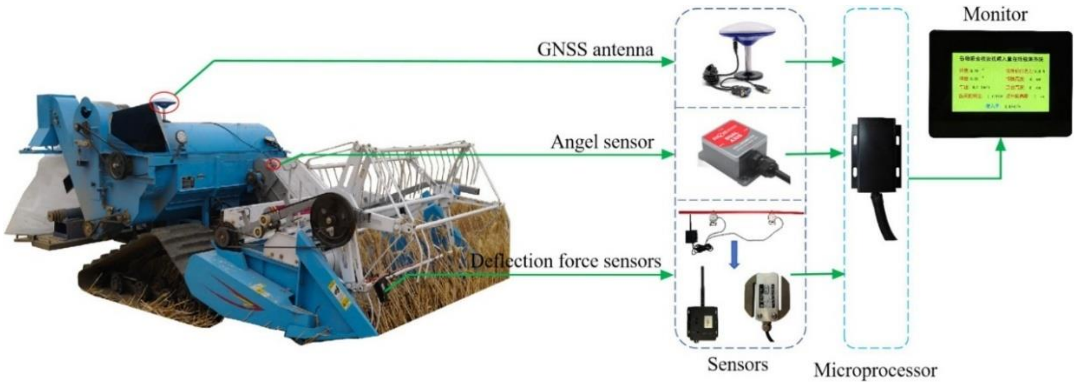


Fig. 10 - Design of the feed rate monitoring system *(Chen et al., 2025)*

Intelligent detection technology

In addition to estimating feed rate based on material pressure measurements during harvesting, advanced intelligent detection technologies such as machine vision and LiDAR can be used for crop perception, enabling crop information collection and prediction. These technologies can estimate crop density and height, thereby indirectly predicting the relationship between crop feed rate and threshing performance.

The measurement principle of a LiDAR system is based on the constant speed of light to calculate the distance between the collision point and the emitted pulse *(Rivera et al., 2023)*. This allows for the determination of target object distance and depth, generating high-precision 3D point cloud data. Studies have shown that two LiDAR sensors can be used for real-time measurement of wheat crop density before harvesting with a combine harvester *(Saeys et al., 2009)*, as well as for analyzing the effects of LiDAR installation angle and height on crop height and density detection *(Blanquart et al., 2020)*.

To enhance LiDAR detection range and efficiency, LiDAR and spectral sensors can be mounted on unmanned aerial vehicles *(Liu et al., 2024)*, allowing for the integration of different data sources to develop a maize canopy height detection method. UAV-mounted spectral sensors offer the advantage of high-speed and efficient crop density detection; however, challenges remain, including high costs, blind spots in small target detection, and susceptibility to adverse environmental factors such as lighting conditions and dust.

With the continuous advancements in machine vision and deep learning technologies, deep learning is not only used for in-field crop and weed density detection *(Adhinata et al., 2024)* but also for crop density assessment during the harvesting period. By equipping harvesters with machine vision technology, crop height and density data can be collected. Additionally, attention mechanisms can be introduced to optimize the backbone structure of neural networks, allowing for image segmentation and object detection of crops. This data, combined with field area measurements, can be used to estimate crop density. *Zhang et al., (2024),* proposed a wheat crop density detection method based on an improved YOLOv5s model (Figure 11), which estimates the height of individual stubble-free wheat plants. Similarly, *Sun et al., (2024),* developed a real-time rice panicle density detection method based on YOLOv5n (Figure 12). By applying coordinate transformation, this approach matches actual crop size with pixel area to calculate rice panicle density, thereby enhancing the harvester's crop state perception capabilities. Machine vision-based crop feed detection offers high accuracy and real-time performance; however, challenges remain, including the high computational cost of deep learning models, difficulties in field deployment, and the requirement for large-scale dataset training.

Fig. 11 - Visual data acquisition system for feed quantity *(Zhang et al., 2024)*

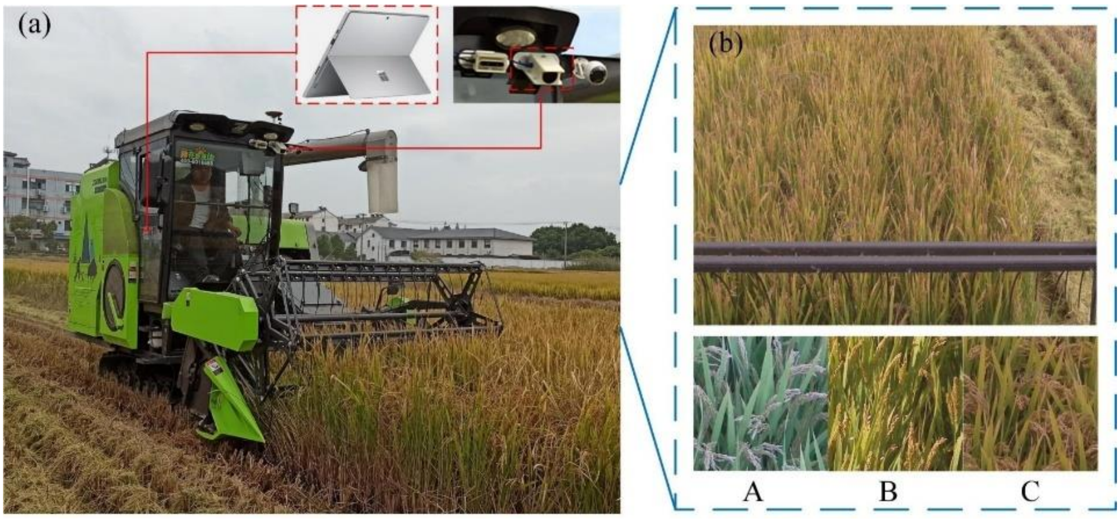


Fig. 12 - Real-time rice spike density detection image acquisition *(Sun et al., 2024)*
(a) acquisition location; (b) sample

In summary, using mechanical sensors for indirect feed rate detection can provide insights into the material flow status within the harvester to a certain extent. However, the collected data lacks predictive capability, requires longer processing times, and is insufficient for providing real-time parameter adjustments for threshing operations. The integration of machine vision-based crop height and density detection methods with YOLO object detection models has proven effective in improving crop feed detection accuracy. Therefore, for crop feed rate detection, a multi-sensor fusion approach incorporating mechanical sensors, machine vision, and LiDAR can enhance environmental adaptability. Additionally, adopting lightweight neural network models combined with transfer learning techniques can reduce reliance on large-scale datasets, improve detection speed, and enhance model generalization capabilities.

Intelligent detection of breakage rate and impurity content

Traditional grain detection methods primarily rely on manual inspection, which is characterized by low efficiency, high error rates, and poor real-time performance. Machine vision and deep learning technologies, with their advantages of non-contact detection, high efficiency, and precise image recognition, provide new approaches for detecting grain breakage rate and impurity content. Machine vision analyzes grain morphological features based on image processing techniques, while deep learning, leveraging the powerful feature extraction capabilities of convolutional neural networks (CNN), integrates object detection, image segmentation, and classification regression methods. These approaches have demonstrated significant superiority in breakage rate and impurity content detection.

Machine vision-based intelligent detection

Machine vision-based grain breakage rate detection primarily relies on morphological, color, and texture feature extraction, as well as spectral imaging analysis, to distinguish between intact and broken grains. In terms of color feature extraction, image processing and feature extraction techniques have been used to calculate the impurity rate of maize kernels, cobs, and husks *(Liu et al., 2022)*. Similarly, *Momin et al., (2017),* performed image segmentation and detection to identify different types of split soybeans, contaminated beans, defective beans, and stems/pods, achieving an identification accuracy of 96% for split beans, 75% for contaminated beans, and 98% for defective beans and stems/pods. Figure 13 illustrates the image processing workflow for grain and impurities in harvested soybeans.

To improve real-time breakage and impurity detection, *Jin et al., (2020),* proposed an online rice breakage rate detection system for combine harvesters based on machine vision. This system identifies broken and intact grains by extracting the chromaticity of kernel images in the color space. Similarly, *Chen et al., (2021),* developed a soybean image acquisition system based on machine vision, achieving a precision rate of 86.45% for breakage rate detection and 85.19% for impurity detection.

Regarding spectral imaging analysis, multi-spectral vision sensors have been employed to obtain spectral bands of pure maize kernels, husks, and straw based on pixel proportions *(Wallays et al., 2009)*. Additionally, by extracting impurity images and spectral features of wheat at different terahertz frequencies, a CNN classification model was developed to process and classify the imaging data, leading to the construction of the V2 CNN wheat image detection model *(Shen et al., 2021).*

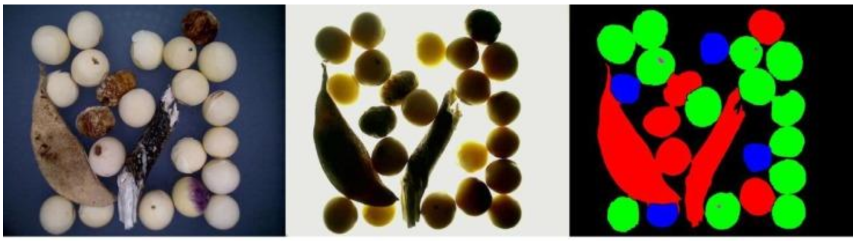


Fig. 13 - Image processing process of soybean harvested seeds with impurities *(Momin et al., 2017)*

Machine vision-based impurity content detection primarily relies on object detection and classification, combined with hyperspectral imaging technology. By utilizing differences in reflectance between grains and impurities across the hyperspectral range, grain impurity detection can be effectively achieved. For instance, *Liu et al., (2023),* introduced a standardized attention mechanism and employed the NAM-EfficientNetV2 network as the grain feature extraction structure. They applied fully convolutional pixel segmentation techniques to segment rice grains and impurities. Similarly, *Zhang et al., (2024),* proposed a wheat breakage rate and impurity rate detection method based on the DeepLab-EDA semantic segmentation model and developed a wheat quality image acquisition system (Figure 14). The DeepLab-EDA model achieved mean intersection over union (MIoU), mean precision (MP), and mean recall (MR) values of 89.41%, 95.97%, and 94.83%, respectively, demonstrating a significant improvement in the accuracy of grain breakage and impurity segmentation.

Additionally, *Chen et al., (2025),* integrated hyperspectral imaging with a random forest (RF) model to achieve rapid and accurate classification of soybean components. The RF classification model achieved optimal prediction accuracy during training, demonstrating its effectiveness in hyperspectral-based impurity detection.

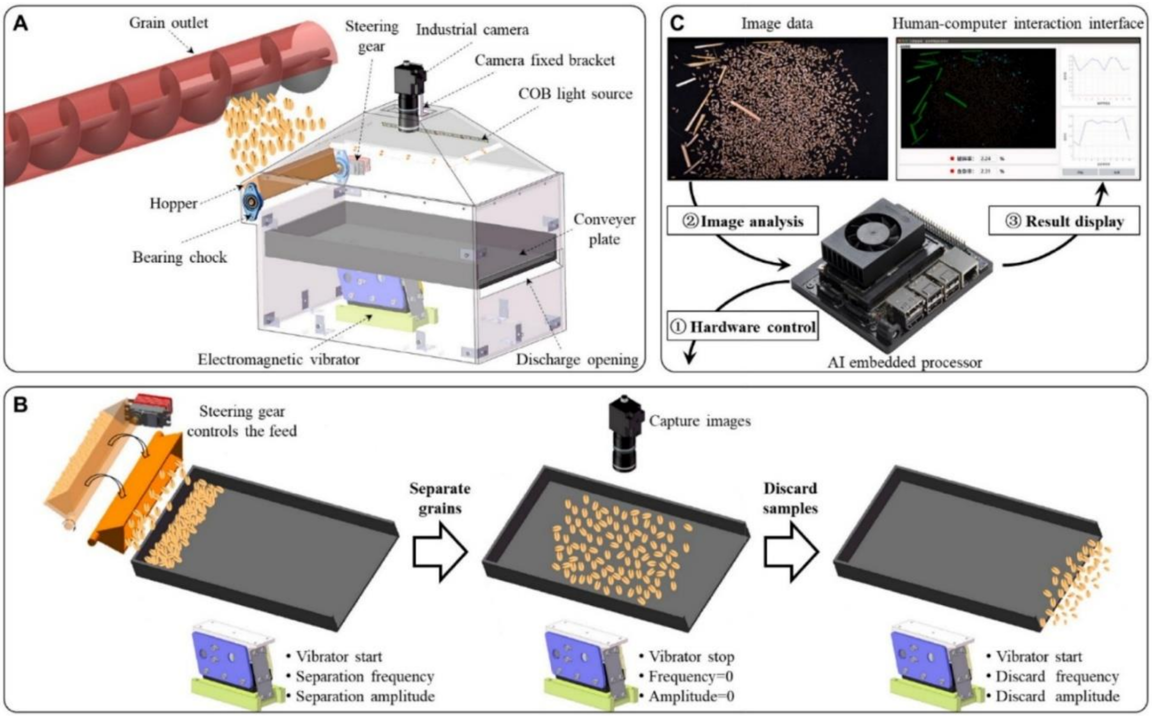


Fig. 14 - Wheat broken rate and impurity rate detection system *(Qi et al., 2024)*

(A) wheat image acquisition device; (B) wheat grain sampling-discarding process; (C) system architecture

Deep learning-based intelligent detection

Deep learning-based grain breakage rate detection primarily utilizes YOLO or Faster R-CNN for object detection, U-Net or Mask R-CNN for image segmentation, and ResNet or VGGNet for feature extraction. These models are used to identify intact and broken grains, accurately segment breakage regions, and extract key features such as the edges, texture, and color of broken grains.

Traditional machine learning methods have relatively weak generalization capabilities for breakage detection. To address this, *Wu et al., (2022),* proposed a maize impurity and breakage rate detection method using feature thresholds and a backpropagation (BP) neural network optimized with a genetic algorithm. The improved Mask R-CNN method demonstrated advantages such as fast detection speed and high accuracy, achieving a maize kernel breakage rate detection time of only 76 ms. *Wang et al., (2023),* enhanced the YOLOv7 model by integrating a transformer encoding block and a coordinate attention mechanism, proposing the BCK-YOLOv7 model for maize kernel breakage detection. Similarly, *Fan et al., (2024),* developed a breakage rate prediction model based on machine vision and machine learning algorithms. In another study, *Wang et al., (2025),* utilized deep learning and sliding window techniques to propose a quantitative model for maize kernel breakage rate detection, named BCK-YOLOv7 (Figure 15). After model deployment, the system achieved a processing speed of 22 FPS, meeting the real-time detection requirements for maize kernel breakage rates. To reduce the computational complexity of detection models, *Wu et al., (2024),* developed a lightweight impurity content and breakage rate detection system based on the Mask R-CNN model (Figure 16). The improved model increased segmentation accuracy for broken particles and impurities by 6.13% and 9.19%, respectively.

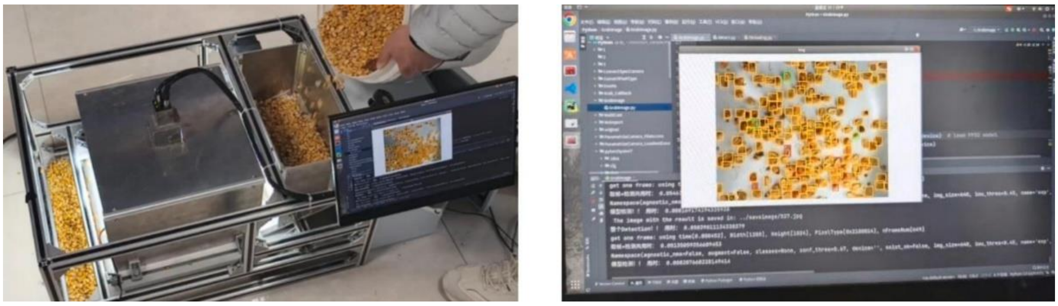


Fig. 15 - Dynamic detection of maize kernels based on BCK-YOLOv7 *(Wang et al., 2025)*

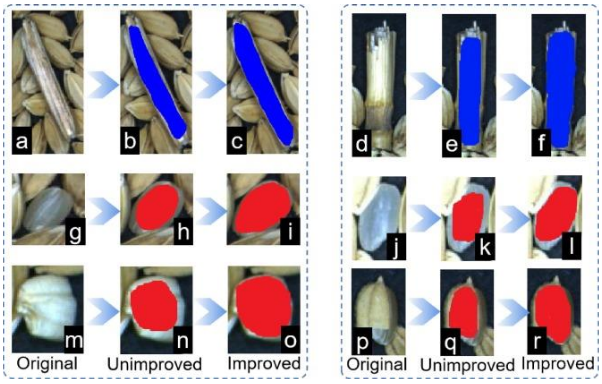


Fig. 16 - Comparison of Detection Performance Before and After Improvement Based on the Mask R-CNN Model *(Wu et al., 2024)*

Deep learning-based impurity content detection primarily employs ResNet or MobileNet for classification, combined with hyperspectral imaging and attention mechanisms to enhance impurity detection accuracy *(Yu et al., 2023)*. *Zhang et al., (2023),* evaluated rice impurity and breakage rates using an improved DeepLabv3+ and YOLOv4 model, achieving higher recognition accuracy compared to existing DeepLabv3+, YOLOv4, U-Net, and BP models. Similarly, *Niu et al., (2024),* developed a lightweight YOLOv8 quality detection model to address issues of fine-grained information loss and low feature representation learning efficiency in YOLOv8, achieving an average recognition speed of 163.9 FPS per image, which is 5.2 FPS faster than the standard YOLOv8 model. *Zhang et al., (2024),* proposed an improved YOLOv8n-based lightweight detection method tailored for small, high-density target detection, achieving impurity and breakage detection accuracies of 95.33% and 96.15%, respectively. Additionally, *Zhang et al., (2025),* introduced a dual-attention diffusion model (DADM) based on a denoising diffusion probabilistic model, which demonstrated superior detection performance on maize, rice, and soybean datasets. This model effectively addresses challenges in agricultural image acquisition caused by seasonal, climatic, and environmental variations, further advancing the integration of deep learning applications in the agricultural sector.

In summary, significant progress has been made in grain breakage rate and impurity content detection using machine vision and deep learning. However, challenges remain, including high data annotation costs, poor real-time performance, and insufficient environmental adaptability. Future research should focus on lightweight deep learning models for integration into harvesters, enabling real-time processing. Additionally, the fusion of multimodal sensors should be explored to enhance the accuracy of grain and impurity recognition.

Intelligent detection of entrainment loss rate

The detection of entrainment loss in the threshing system is primarily used to evaluate threshing quality. Current research on entrainment loss monitoring mainly involves installing entrainment loss monitoring sensors beneath the threshing drum to analyze the correlation between the number of maize kernels detected by the sensors and the actual entrainment loss *(Bomoi et al., 2022)*. This approach enables indirect monitoring of entrainment loss. For entrainment loss detection, the YT-5L piezoelectric ceramic element is commonly used as a sensing component to develop grain loss monitoring sensors. The performance of these sensors is evaluated by analyzing the voltage amplitude and signal attenuation time of grain impact events. Additionally, operational parameters such as feed rate and drum speed influence the proportional relationship between sensor measurements and actual entrainment loss.

Liu et al., (2023), designed an entrainment loss detection system for direct maize grain harvesting based on an embedded microcontroller. The system exhibited a maximum detection error of 9.96% and an average error of approximately 6.52%. Similarly, *Dong et al., (2024),* symmetrically installed two entrainment loss monitoring sensors along the radial direction of the threshing drum and developed a maize entrainment loss monitoring model using a multiple linear regression machine learning algorithm. Figure 17 illustrates the structure and signal processing workflow of the entrainment loss monitoring sensor.

Furthermore, *Dong et al., (2024),* designed another entrainment loss detection system (Figure 18) and implemented a random forest machine learning algorithm to construct a loss prediction model, significantly improving entrainment loss estimation accuracy. To further enhance detection precision and practical application, *Yu et al., (2025),* identified that the optimal placement of the detection sensor was at the left tail end of the concave sieve, with a minimum distance of 58 mm between the sensor plate centerline and the concave sieve, and an installation angle of 65° relative to the horizontal plane, achieving the highest detection accuracy.

In summary, current entrainment loss detection models are relatively simplistic, often neglecting dynamic operating conditions such as feed rate and drum speed variations. This limitation results in significant fluctuations in sensor measurement errors, reducing detection accuracy. Additionally, the adaptability of sensor installation positions and structures remains insufficient, and the vibration characteristics of combine harvesters during field operations significantly impact sensor performance. With the accumulation of entrainment loss detection data, the integration of multi-sensor fusion and deep learning models can enhance noise suppression and real-time analysis capabilities, enabling the development of a more precise and reliable loss monitoring system.

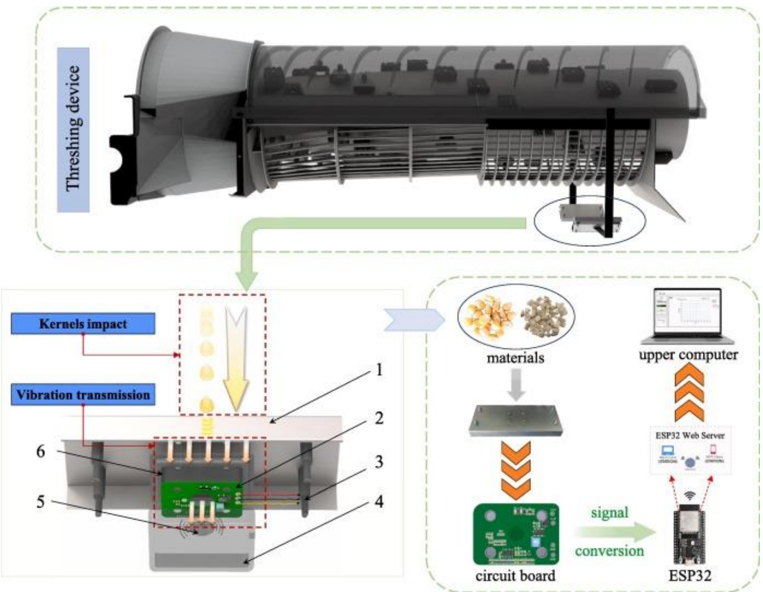


Fig. 17 - Structure and signal processing workflow of the entrainment loss monitoring sensor *(Dong et al., 2024)*
1.Sensor sensitive plate; 2. Circuit board; 3. Sensor fixing bolt; 4. Circuit board protector; 5. Piezoelectric ceramic; 6. Damping material

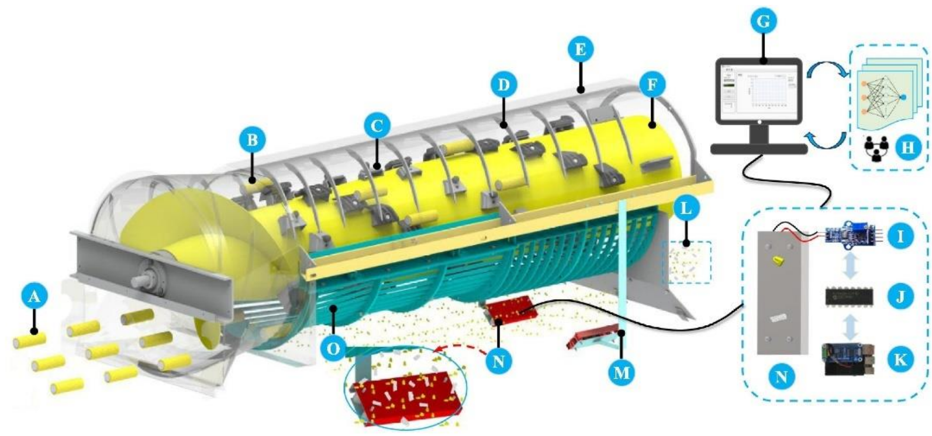


Fig. 18 - Schematic diagram of the entrainment loss monitoring system components *(Dong et al., 2024)*

(A) Maize Conveying; (B) Maize Threshing; (C) Threshing Elements; (D) Guide Vanes; (E) Threshing Cover; (F) Threshing Drum; (G) Display; (H) Classification Model; (I) Charge Amplification Module; (J) AD Converter Module; (K) Controller; (L) Entrainment Loss Material; (M) Sensor Mounting Bracket; (N) Sensor; (O) Concave Threshing Plate

Intelligent threshing control

Based on the structural innovations of threshing devices, the detection of operational parameters such as rotational speed, vibration, and torque, as well as machine vision-based detection of breakage rate and impurity content, a solid structural and data foundation has been established for intelligent control of the threshing system. Intelligent control technologies leverage algorithms such as fuzzy control, neural networks, and reinforcement learning to achieve dynamic adjustment of parameters including drum speed, concave clearance, and feed rate *(Wang et al., 2025)*, thereby enhancing the threshing system's adaptability to multiple crops and improving threshing efficiency.

For intelligent control of maize threshing systems, the primary objective is to address the challenges of high grain breakage and entrainment loss rates during high-moisture maize harvesting under complex and time-varying operating conditions. *Li et al., (2023),* developed an automatic low-loss maize grain harvesting control system and optimized a control model for drum speed, concave clearance, and driving speed using an improved particle swarm optimization algorithm.

Additionally, some researchers have designed optimal control models based on feed rate and threshing gap. For instance, *Fan et al., (2022),* developed a threshing device equipped with an automatic gap adjustment system based on feed rate. Their results showed that the variable-gap threshing system outperformed fixed-gap systems in terms of efficiency under random feed rate fluctuations.

Moreover, variations in field conditions and crop density can cause fluctuations in the combine harvester's feed rate. To address this, *Fan et al., (2023),* proposed a multi-parameter maize threshing control structure and method based on feed rate (Figure 19). By applying intelligent algorithms, a control model was developed for drum speed, threshing gap, and cover vane angle, which enhanced the adaptability of the threshing system to different crop conditions.

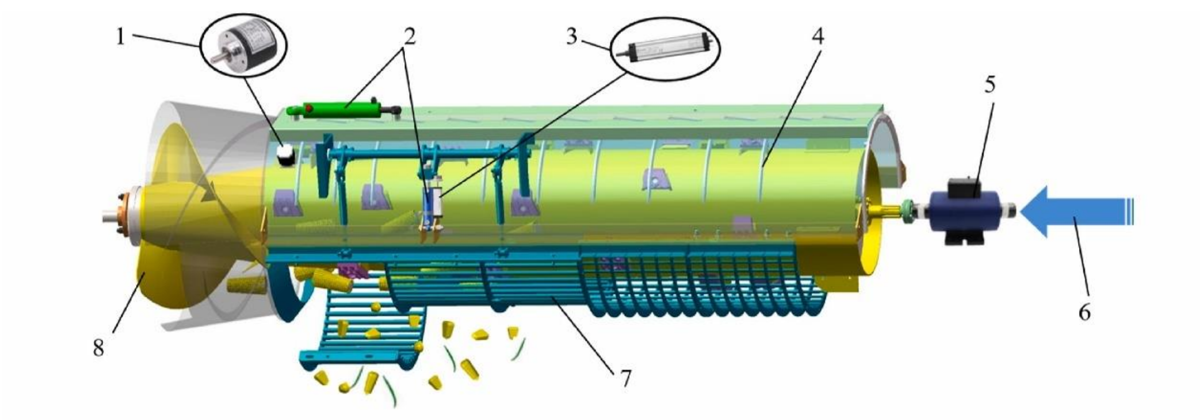


Fig. 19 - Hardware of the multi-parameter control system for maize threshing *(Fan et al., 2023)*

1. Angle sensor; 2. Hydraulic cylinder; 3. Displacement sensor; 4. Guide vane; 5. Dynamic torque sensor; 6. Hydraulic motor drive; 7. Concave; 8. Rotor

For intelligent control of cereal threshing systems, machine learning models have been applied to construct predictive models, effectively addressing the challenges of time variability, delay, and multi-parameter coupling in cereal threshing. These models provide a foundation for intelligent control of the threshing process. For example, *Ma et al., (2023),* developed an artificial neural network (ANN) model to predict the performance of a flexible threshing device. Similarly, *Li et al., (2024),* proposed a fusion approach combining particle swarm optimization and wavelet neural networks to optimize the state-space model of the threshing system. They employed model predictive control (MPC) to regulate multiple threshing parameters. The resulting state-space and adaptive control models demonstrated strong adaptability and stability for threshing system operation.

In summary, control technologies for intelligent threshing systems are developed based on structural innovations in threshing devices and the detection of operational parameters, providing both structural and data support for intelligent regulation. Methods such as fuzzy control and neural networks have been widely applied for the dynamic adjustment of threshing system operating parameters.

THRESHING SYSTEM DEVELOPMENT TRENDS

Multi-sensor fusion and intelligent detection

The multi-sensor fusion used for detecting operating parameters and operation quality in threshing systems still faces numerous challenges, including spatiotemporal synchronization, accuracy and robustness, real-time performance, and compatibility, making it difficult to provide stable and precise data. Therefore, for intelligent threshing systems, it is necessary to construct a multi-sensor fusion detection network utilizing various sensors such as infrared, laser, ultrasonic, and spectral sensors to enhance data accuracy.

Additionally, data synchronization mechanisms should be introduced, and intelligent filtering algorithms as well as deep learning methods should be applied to further improve data analysis and processing capabilities. Standardization of sensor data formats and communication protocols should also be established, along with the development of large-scale datasets for crop harvesting operations, to enhance the generalization capability of intelligent detection models.

Deep learning and intelligent algorithm optimization

Deep learning technology has demonstrated exceptional pattern recognition capabilities in the optimization of threshing operation parameters and quality detection. It significantly enhances the automation of key tasks such as grain loss prediction, breakage rate detection, impurity identification, and operational condition optimization. However, challenges remain, including limited availability of harvesting data samples, high data annotation costs, poor adaptability to different crops and field environments, and difficulties in integrating deep learning with threshing system control strategies.

Therefore, under the premise of multi-sensor fusion, the adoption of lightweight deep learning models is essential to enhance edge computing capabilities. In addition, the application of transfer learning and related techniques can promote the development of threshing operations toward higher precision, intelligence, and adaptability.

Intelligent control of threshing systems

Intelligent threshing control systems for combine harvesters still face core challenges such as difficulties in real-time control, poor crop adaptability, and complex multi-parameter coupling. Traditional control methods, including PID and fuzzy control, struggle to achieve precise regulation under complex and dynamically changing threshing conditions, often resulting in high levels of threshing loss, grain breakage, and impurity content.

Deep learning, through data-driven approaches, can predict optimal adjustment strategies for threshing parameters. When integrated with physical modeling, it enables the construction of reinforcement learning-driven intelligent adaptive control systems that autonomously adjust control parameters based on different crops and field environments. In the future, with the advancement of technologies such as digital twins, threshing control systems will become more precise and intelligent, further promoting the development of agricultural machinery toward unmanned operation and autonomous optimization.

CONCLUSIONS

The structural design of threshing devices in combine harvesters has been significantly optimized by fully considering crop characteristics and variations in operating conditions, resulting in enhanced multi-crop adaptability, improved threshing efficiency, and greater operational stability. At the same time, real-time monitoring technologies based on multi-sensor fusion, machine vision, and deep learning models have achieved major breakthroughs in key aspects such as feed rate detection, grain breakage rate analysis, impurity content assessment, and entrainment loss identification, providing high-precision data support for the intelligent regulation of threshing systems.

Moreover, adaptive control strategies based on fuzzy logic have laid the foundation for developing data-driven control systems with multiple inputs and outputs for threshing systems. Reinforcement learning methods are increasingly being adopted to enable real-time adjustment of threshing parameters in response to changing environmental conditions, ensuring that the system operates under optimal conditions—an emerging and important direction in the intelligent development of combine harvesters.

However, despite substantial technological progress, challenges remain in the online monitoring and dynamic regulation of threshing system operation parameters and quality indicators. In the future, with the further integration of artificial intelligence and deep learning into combine harvester threshing systems, the capabilities of intelligent perception, decision-making, and control will be significantly enhanced, ultimately enabling the construction of a low-loss, high-efficiency intelligent threshing system.

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