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# A review on advanced sensing technologies for real-time monitoring of grain loss

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**Abstract**
Grain loss during combine harvesting is a critical issue influenced by various factors. Since the 1960s, researchers have developed automated detection systems using piezoelectric sensors to monitor grain wastage. However, existing sensors struggle with saturation at high impact rates. To improve detection accuracy in rice harvesting, laboratory experiments were conducted to refine the structure and placement of the instrumented plate. The optimal plate (150×40×1 mm) successfully measured grain loss with an error margin of less than 3.83%. From 2017 to 2020, field experiments in Northeast China analyzed grain dry Matter Loss (GDML) and Mechanical Losses (ML), Including Header Loss (HL), Cleaning Loss (CL), Entrainment Loss (EL), and Un-Threshed Loss (UTL). The results showed that harvesting at 52-53 days after heading (DAH) for long-grain rice and 53-54 DAH for short-grain rice significantly reduced losses. In addition, smart farming technologies, such as the Internet of Things (IoT) and machine learning, enhance precision agriculture by improving yield prediction, pest monitoring, and harvest scheduling. Furthermore, smartphone-based imaging provided a quick, non-invasive method for assessing Grain Moisture Content (GMC). In Malaysia, studies recorded grain losses ranging from 1.08% to 1.21%, negatively impacting farm profits. By optimizing harvesting schedules, fine-tuning machine parameters, and integrating intelligent farming techniques, grain loss can be significantly minimized, operational efficiency can be improved, and economic returns for farmers can be maximized.

**Keywords:** IoT, combine harvester, grain loss, rice harvesting, smart farming, machine learning

## 1. Introduction
Agriculture plays a crucial role in global food security, and the efficiency of grain production significantly impacts both economic stability and sustainability (Blanco, 2016) [4]. However, one of the persistent challenges faced by the agricultural sector is grain loss, which occurs at various stages of harvesting, threshing, transportation, and storage. Grain loss not only affects farmers' profitability but also contributes to food scarcity and increased production costs. In traditional farming practices, losses were often estimated through manual methods, which were time-consuming, prone to errors, and lacked precision. The emergence of advanced grain loss sensing technologies has revolutionized this domain, offering real-time monitoring, automation, and improved accuracy in minimizing grain loss (Yang, 2012) [28].
Grain loss can be categorized into pre-harvest, harvest, and post-harvest losses, each of which contributes to a significant reduction in overall yield. (Craessaerts, 2010) [6]. Pre-harvest losses may result from pests, diseases, or adverse weather conditions, while harvest and post-harvest losses often straw from mechanical inefficiencies i.e. over loading of the machinery, improper cleaning of the blades, moisture content of the grain, improper handling, or inadequate storage facilities (Zhenwei, 2016) [30]. Traditional methods of estimating grain loss involved manual sampling and visual inspection, which were both labor-intensive and unreliable. This created a pressing need for automated and intelligent grain loss detection systems that could provide real-time insights and corrective measures. The integration of sensor-based monitoring, data analytics, and machine learning has proven to be a good invention in this field (Spokas, 2016) [26].
Recent technological advancements have enabled the development of highly efficient grain loss detection mechanisms. Various types of sensors, including optical, acoustic, capacitance, and IoT based smart sensors, have been introduced to enhance accuracy and precision in detecting grain loss.

These advanced sensors are capable of monitoring machine performance, detecting foreign particles, assessing grain flow, and minimizing wastage during harvesting and processing. Optical sensors use laser-based or infrared sensors to detect grain losses by analyzing the amount of grain passing through a harvester, providing real-time visual feedback to operators for quick adjustments.

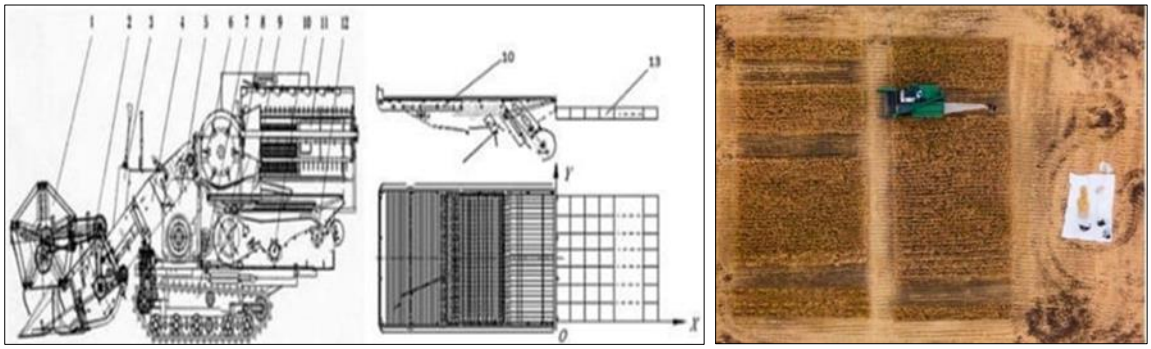

**Fig 1:** The harvesting machine used for the field harvesting

**Fig 2:** Grain threshing separation process under highspeed camera

Acoustic sensors operate by detecting sound variations caused by grain impact and are highly effective in threshing and winnowing operations, where grain separation efficiency is crucial. Capacitance sensors work on the principle of electromagnetic field changes, detecting moisture content, foreign matter, and grain spillage. IoT-based smart sensors enable continuous monitoring and remote data collection through wireless communication networks and can be integrated with mobile applications and cloud-based platforms for real-time loss assessment. The incorporation of artificial intelligence (AI) and machine learning (ML) in grain loss detection has further enhanced precision and efficiency.

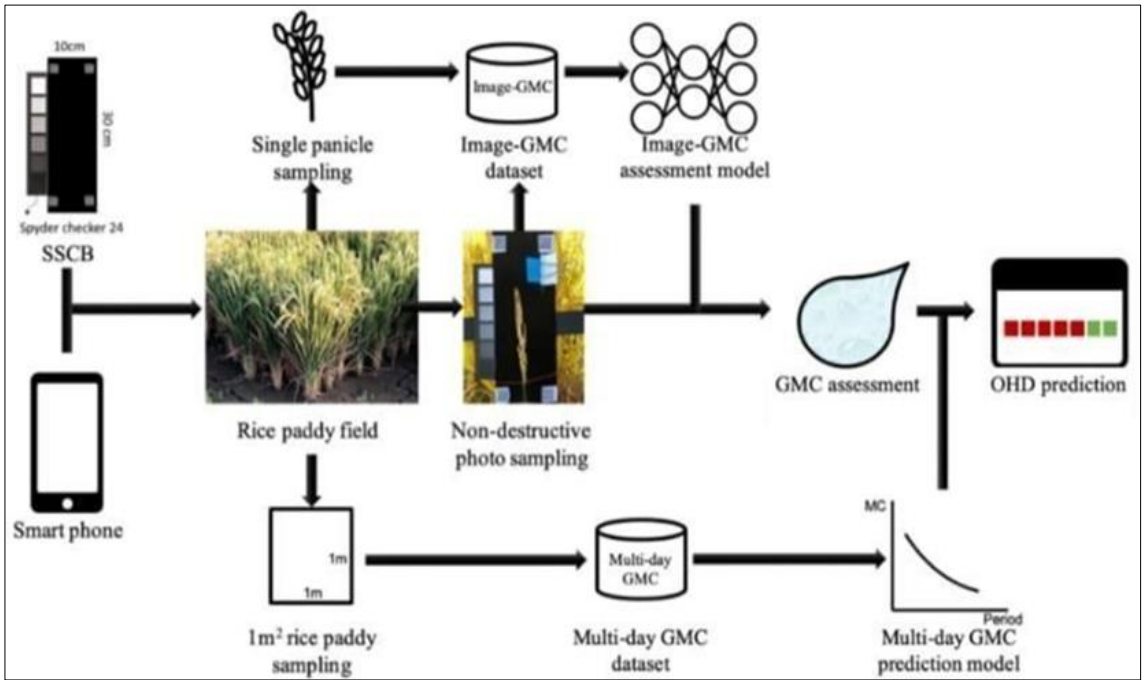


**Fig 3:** Research process and scenarios (Ming, 2021)

AI algorithms analyze sensor data, predict loss patterns, and suggest automated corrective measures. Machine learning models use historical data to improve decision-making, reducing human intervention while maximizing productivity (Zhang, 2007) [7], AI-driven predictive maintenance ensures that harvesting equipment operates at optimal efficiency, minimizing grain loss due to mechanical failures. Despite the significant progress in grain loss sensing technologies, several challenges remain. The high initial investment required for installing and maintaining advanced sensing systems can be prohibitive for small-scale farmers.

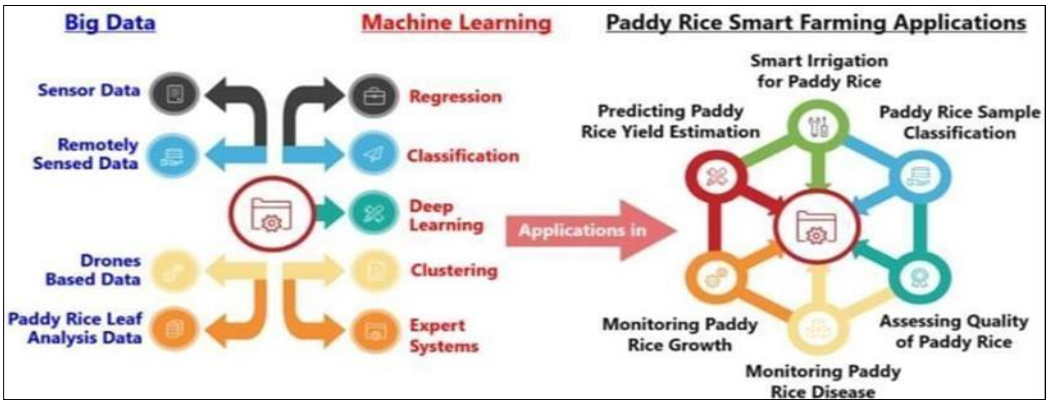


**Fig 4:** Data analysis of grain loss in field (Carter, 2010) [5]

The operation of AI-integrated sensors and IoT-based systems requires skilled labor and adequate training. Large volumes of data generated by smart sensors need advanced processing systems and efficient storage solutions. External factors such as dust, humidity, and temperature fluctuations can affect sensor accuracy. The future of grain loss sensing technologies is promising, with ongoing research focusing on enhanced automation, real-time analytics, and AI-driven precision farming. The development of cost-effective and scalable solutions will make these technologies more accessible to farmers worldwide. The integration of blockchain technology could further enhance transparency in grain monitoring and supply chain management. Additionally, satellite-based remote sensing and UAV (Unmanned Aerial Vehicle) monitoring hold potential for improving grain loss detection at a larger scale. In conclusion, the adoption of advanced grain loss sensing is essential for optimizing yield, improving resource efficiency, and ensuring global food security (Laamrani, 2018) [19].

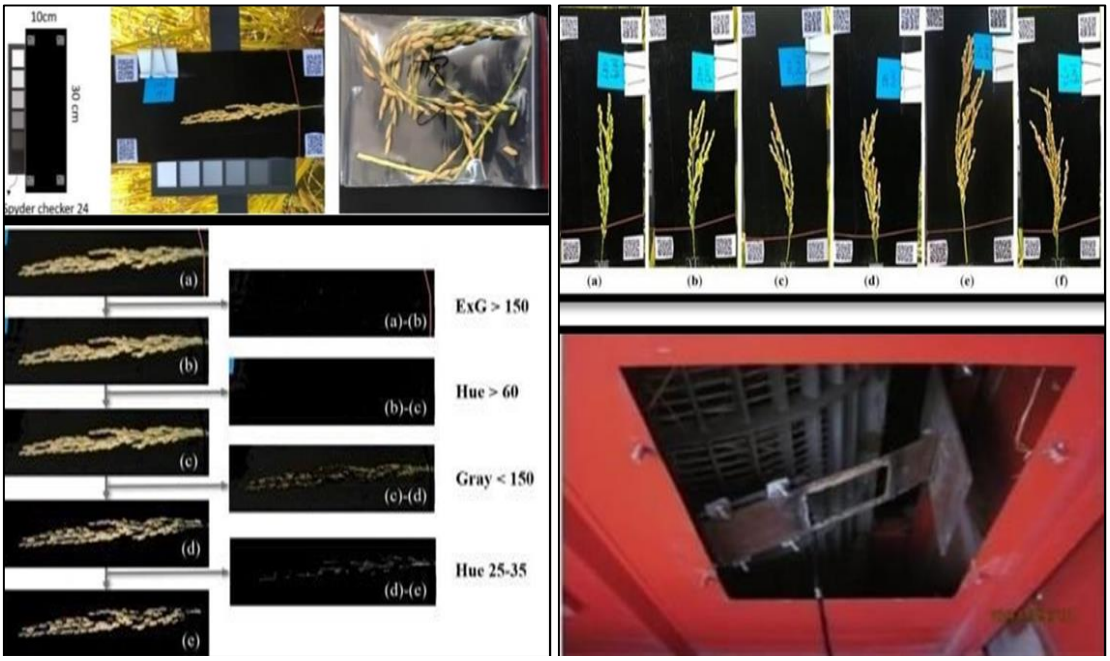


**Fig 5:** Image recognition of moisture content in paddy straw for different trails

Continued research and technological advancements will pave the way for a more sustainable and efficient agricultural ecosystem. The widespread implementation of these innovative solutions will ultimately enhance grain recovery, reduce waste, and increase profitability for farmers and stakeholders in the agricultural industry.

## 2. Grain Loss Detection

Grain loss in agricultural production is a critical issue affecting global food security and economic stability. In a combined harvester, grain loss occurs at various stages, including pre-harvest, harvesting, and post-harvest handling. These losses result from inefficient harvesting techniques, mechanical inefficiencies, and environmental factors,

leading to significant economic losses for farmers and a reduction in overall food availability. According to research, post-harvest grain losses range from 5% to 15% globally, with developing countries facing even higher losses due to inadequate storage and handling techniques. Reducing grain loss through advanced sensing and mitigation strategies can enhance food security by maximizing yield utilization while minimizing economic and environmental burdens.

### 2.1 Pre-Harvest Stage

Grain loss at this stage is influenced by pest infestations, crop diseases, lodging (crop falling before harvest), and unfavorable weather conditions such as droughts, storms, or heavy rainfall. Poor agronomic practices, improper fertilization, and delayed harvesting further contribute to yield reduction. If crops are not harvested at the right maturity stage, losses due to shattering (grain dropping before harvest) can increase. Research indicates that pre-harvest grain losses can range between 2% to 5%, depending on crop variety and environmental conditions.

### 2.2 Harvesting Stage

The harvesting process is one of the most crucial phases where significant grain loss occurs due to improper harvester settings, mechanical failures, and operator errors. In a combined harvester, losses primarily happen due to threshing inefficiencies, separation failures, and uncollected grains falling to the ground. Factors such as improper cutter bar height, incorrect drum speed, and misaligned concave settings can contribute to excessive losses. Additionally, over-threshing can lead to grain breakage, reducing market quality, while under-threshing results in unthreshed grains being discarded along with crop residues. Studies suggest that harvesting-related losses account for 3% to 8% of total grain production.

### 2.3 Post-Harvest Handling Stage

Once grains are harvested, they undergo multiple handling processes, including transportation, drying, storage, and processing. Each step introduces risks of additional losses due to inefficient handling techniques, poor storage conditions, and biological degradation. Inadequate drying can lead to fungal contamination and mycotoxin production, affecting both yield and food safety. Improper storage conditions result in losses due to insect infestations, rodent attacks, and mold growth. Mishandling during transportation and inefficient processing methods also contribute to further reductions in usable grain. Research suggests that post-harvest losses can range between 5% to 15%, with developing nations experiencing even higher losses due to inadequate infrastructure (Nath, 2017) [22]. Addressing these losses through advanced sensing technologies, improved harvesting machinery, and better storage solutions is essential to ensure efficient grain utilization as shown in Fig. 6. Implementing real-time grain loss detection systems in combined harvesters can help minimize losses by providing instant feedback to operators, allowing for immediate adjustments in machine settings. Additionally, adopting better drying, storage, and transportation methods can significantly reduce post-harvest losses, improving both farmer profits and overall food security (Adisa, 2016) [1].

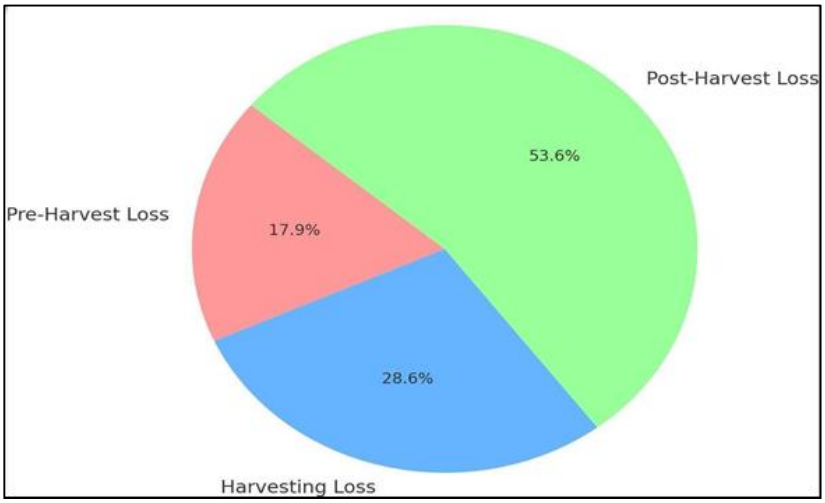


**Fig 6:** Grain loss distribution at different stages

## 3. Optical Sensors for Grain Loss Monitoring

Traditionally, grain loss assessment has relied on manual techniques such as hand sampling, visual inspection, and estimation based on collected residues in the field. These conventional methods are labor-intensive, time-consuming, and susceptible to human error. Additionally, environmental variability and differences in harvesting machinery performance further complicate accurate assessment. A major limitation of traditional techniques is the lack of real-time feedback, which prevents farmers from making immediate adjustments to their harvesting processes, thereby exacerbating losses. To overcome these challenges, modern agricultural technology has introduced various sensor-based approaches that significantly enhance grain loss detection accuracy. Optical sensors utilize light-based detection to analyze the amount of grain passing through harvesting equipment and detect loss patterns (Krishna *et al*., 2024) [16]. Acoustic sensors detect sound variations caused by grain impact, helping to optimize the harvesting process (Cheng, 2022) [8]. Capacitance sensors differentiate between collected and lost grains by measuring their dielectric properties, providing real-time assessment. Furthermore, IoT-based sensors integrate with smart farming systems to continuously monitor and transmit grain loss data to cloud-based platforms for comprehensive analysis, enabling more efficient decision-making in grain handling (Elgendy, 2022) [11].

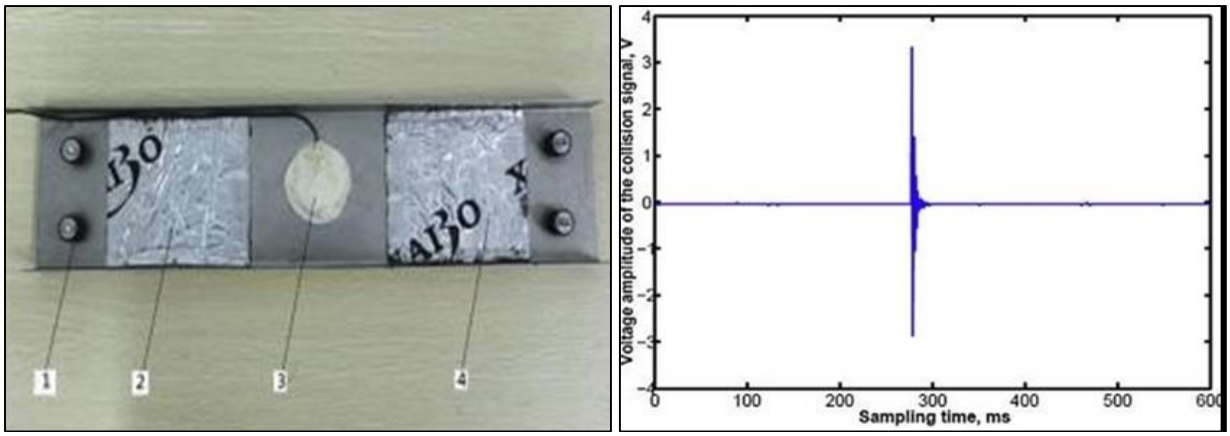


**Fig 7:** Optimal position of damping layer and collision signal waveform. 1. Rubber shock absorber, 2. Viscoelastic material layer 1, 3. Piezoelectric ceramic, 4. Viscoelastic material layer

Since there is always an initial force acting on the contact area in the impact process, and grain moves along the instrumented plate, analyzing the impact process as a vibration system is more reasonable. This approach transforms the impact problem into solving a vibration system response with a given initial velocity input. According to the Passion-Kirchhoff flat-plate theory, the natural frequencies and vibration modes of an instrumented plate primarily depend on its thickness, length, and width. Therefore, selecting the optimal geometry of the instrumented plate is a key design process to enhance the sensor's performance. Research indicates that low orders of vibration have a more significant effect on the dynamic performance of the structure. A higher first-order natural frequency allows the system to reach a steady-state faster, while greater vibration displacement leads to more deformation of the piezoelectric element, thus generating a higher amount of electric charge and increasing sensor sensitivity. To determine the first-order natural frequency and relative deformation rate under various structures, modal analysis is often conducted using advanced simulation tools like SolidWorks (Nakra, 1998) [21].

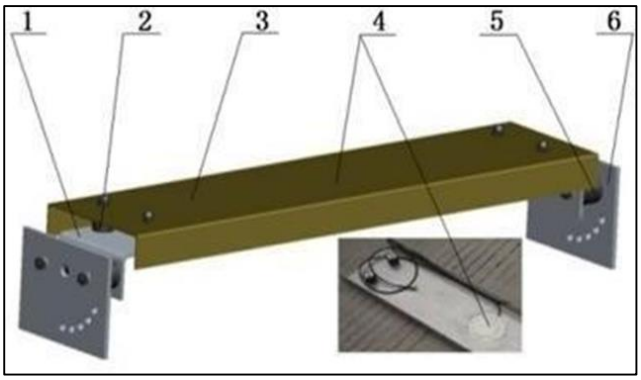


**Fig 8:** Structure of grain loss monitoring sensor, 1. Support plate, 2. Rubber shock absorber, 3. Sensitive plate, 4. Circular piezoelectric ceramics 5. Rubber shock absorber 2, 6. Rack connection par

To verify software simulation results and analyze the impact plate structure's effect on detection performance, single-grain impact experiments have been conducted in laboratory settings. These experiments involve mounting an instrumented piezoelectric element on a specialized plate and dropping single grains from a specific height. The signals generated during impact are processed by a charge amplifier, and the voltage signals are recorded using a digital storage oscilloscope. Experiments conducted with freshly harvested rice grains (moisture content of approximately 25.02% and a thousand-grain weight of 26.92 g provide valuable insights into optimizing sensor configurations for better grain loss assessment in real-world harvesting conditions (Lenaerts, 2012) [20].

By integrating traditional and modern methods, the accuracy and efficiency of grain loss assessment can be significantly improved. The adoption of advanced sensor technologies and vibration analysis techniques not only enhances grain recovery but also contributes to sustainable agricultural practices by minimizing waste and improving overall productivity (Qiao, 1992) [23]. Studies on characteristics of material mechanics of rice grains. Further research and development in this area will be instrumental in refining these technologies for widespread implementation in modern farming systems.

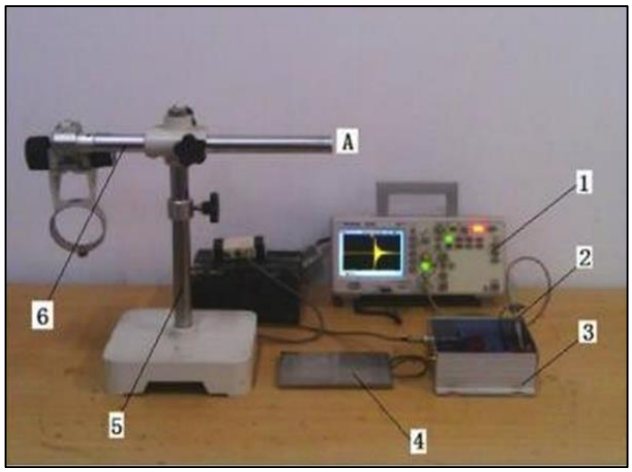


**Fig 9:** Single grain impact experimental system. A. Grain release point, 1. Storage digital oscilloscope, 2. Probe, 3. Signal processing circuit, 4. Grain loss sensor, 5. Support bar, 6. Height adjustment bar

## 4. Working Mechanisms of Grain Loss Sensors

Each sensor technology operates based on specific principles to detect and quantify grain loss accurately. Optical sensors use light reflection and absorption principles to identify missing grains, while acoustic sensors rely on sound wave patterns to differentiate between collected and lost grains. Capacitance sensors measure the electrical properties of grains, providing precise loss estimates. (Laamrani, 2018; Krishna *et al.*, 2024) [19].

IoT-enabled sensors allow real-time monitoring, integrating with data analytics platforms for improved decision-making. These technologies offer more precise and timely data than traditional manual methods, ensuring better loss management and improved yield optimization.

## 5. Integration of AI, IoT and Machine learning in grain loss prevention

The combination of AI, IoT, and ML has revolutionized grain loss detection. AI-powered algorithms analyze large datasets collected from sensors to identify loss patterns and predict potential issues before they occur. IoT-enabled devices connect different components of harvesting machinery, allowing farmers to access real-time data through mobile applications or cloud-based platforms. Machine learning models continuously improve detection accuracy by learning from previous data, enabling automatic adjustments in harvesting machinery to minimize grain loss (Tripathi, 2023) [27]. This integration significantly enhances the efficiency of grain loss monitoring and provides actionable insights to farmers (Rehman, 2019) [24].

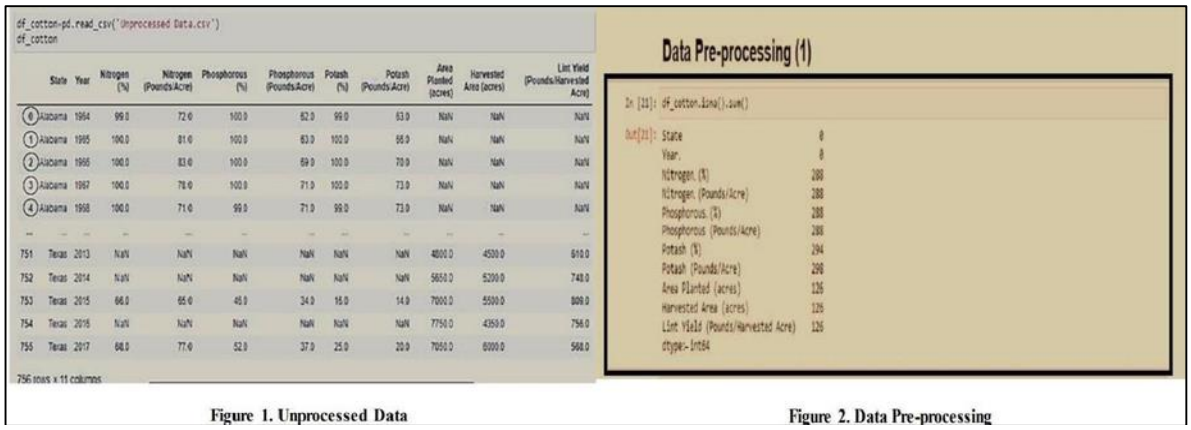


Figure 1. Unprocessed Data

Figure 2. Data Pre-processing

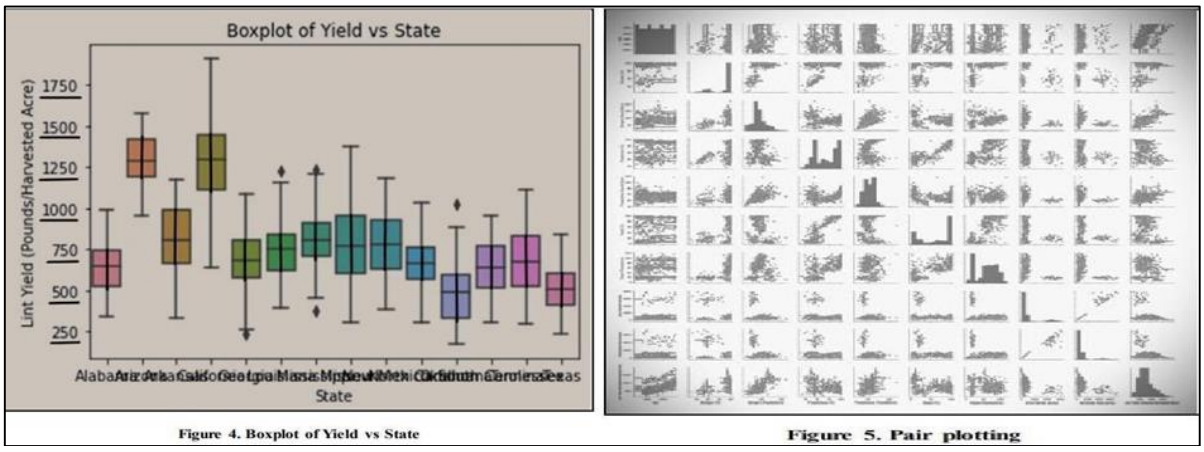


Figure 4. Boxplot of Yield vs State

Figure 5. Pair plotting

**Fig 10:** Data model collection of crop residue

## 6. Future trends and innovations in grain loss detection

The future of grain loss sensing lies in further advancements in AI, remote sensing, and automation. Emerging technologies such as drone-based monitoring, satellite imaging, and robotic harvesting systems are expected to revolutionize grain loss detection (Alizadeh, 2013) [2]. AI-driven predictive maintenance will enable machinery to self-adjust based on real-time loss data, reducing waste and increasing operational efficiency. Blockchain technology may also play a role in enhancing traceability and accountability in grain production and storage. As research in this field progresses, innovative solutions will continue to enhance grain loss detection and prevention.

**Fig 11:** Installation position of the sensor and image of the field tests (Alizadeh, 2013) [2]

## 7. Challenges in implementing advanced grain loss sensing

There are several challenges hinder its widespread adoption. The high initial cost of acquiring and installing sensor-based systems is a major barrier for small-scale farmers (Carter, 2010) [5]. Additionally, technical expertise is required to operate and maintain these advanced systems, which may not be readily available in rural agricultural settings. Environmental factors such as dust, humidity, and temperature variations can also affect sensor performance, reducing accuracy and reliability (Tripathi, 2023) [27]. Addressing these challenges through cost-effective solutions and farmer training programs will be essential for the successful implementation of these technologies.

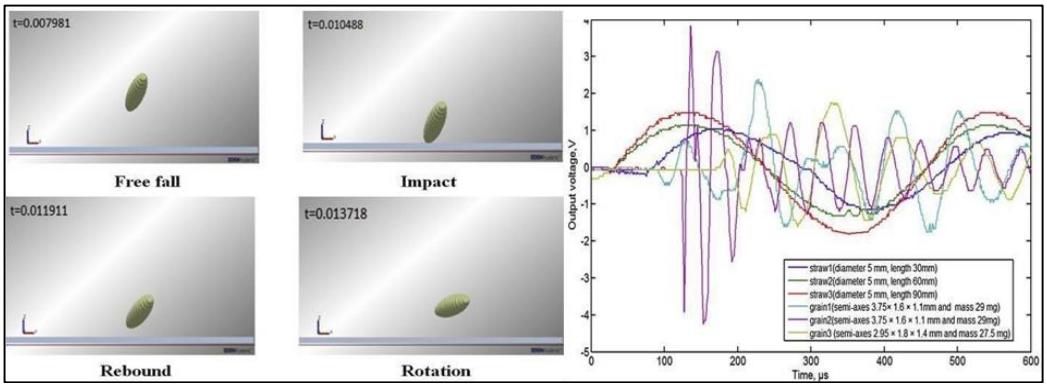


**Fig 12:** Typical experimental results of rice grain and MOG collision with the sensor (Alizadeh, 2013) [2]

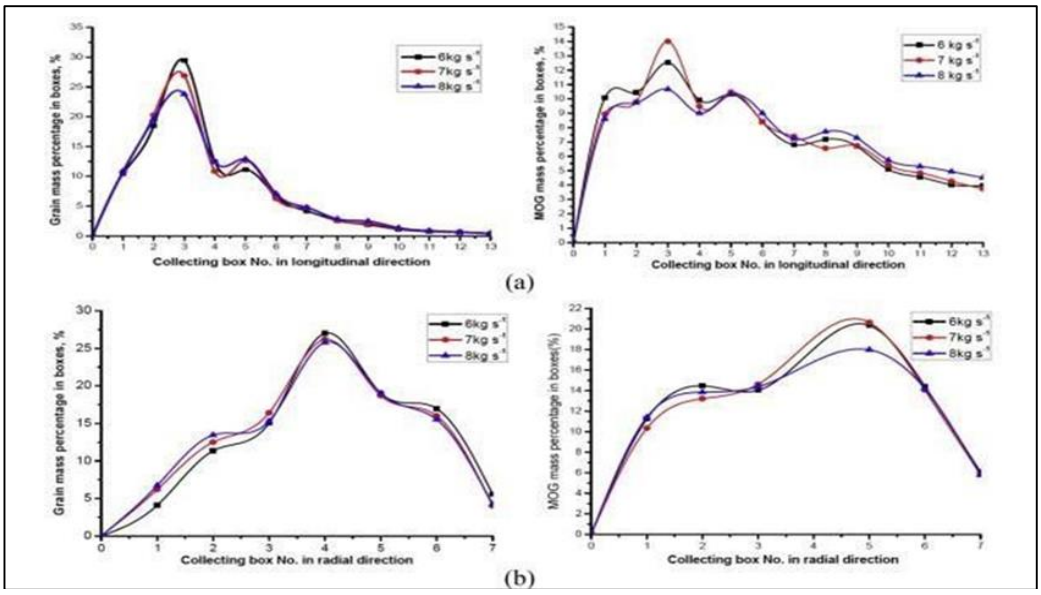


**Fig 13:** Grain and Moisture of grain distribution curves along axial-flow threshing rotor and radial direction of threshing rotor; (a) longitudinal direction, (b) radial direction (Alizadeh, 2013) [2]

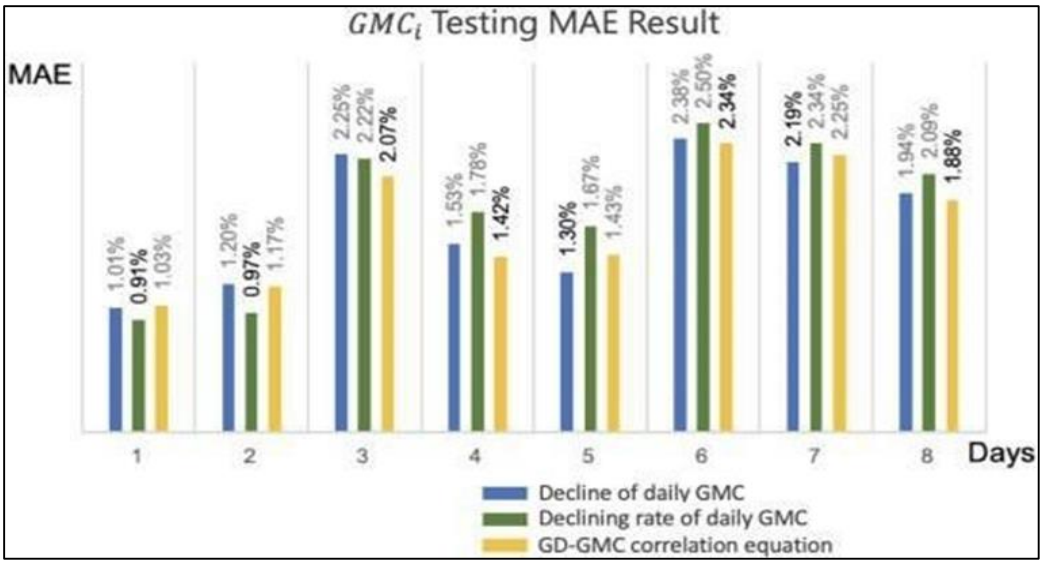


**Fig 14:** Testing of the moisture content (Missotten, 2020) [10]

## 8. Conclusion

Advanced grain loss sensing technologies have transformed the way farmers detect and mitigate grain losses. The integration of optical, acoustic, and IoT-based sensors, combined with AI and machine learning, has improved accuracy and real-time monitoring. However, challenges such as high costs and environmental limitations must be addressed to ensure wider adoption. Future advancements in remote sensing, automation, and AI-driven analytics will further enhance the efficiency of grain loss detection systems. Encouraging research, investment, and training in these technologies will help maximize agricultural productivity while reducing food waste, ultimately contributing to global food security.

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