

Smart Grain Analysis Using IOT and CNN

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Peer Review Information	Abstract
<p>Type: Article Received: 10 February 2026 Revised: 12 March 2026 Accepted: 18 April 2026 Published: 23 May 2026</p>	<p>Food safety, storage management, and agricultural commerce all depend on the evaluation of grain quality. Grain inspection is still done by hand in many places using basic laboratory testing techniques or visual observation. These conventional methods are subjective, time-consuming, and frequently lead to uneven grading. Farmers may experience unfair pricing and post-harvest losses as a result of this. Automated systems that can provide precise and real-time grain quality evaluation are therefore becoming more and more necessary. The smart grain analysis system presented in this paper combines CNN-based image processing with Internet of Things (IoT) sensing. Grain image capture and automated quality classification are done by the system using a Raspberry Pi device. IoT sensors are used simultaneously to monitor environmental parameters like temperature, humidity, moisture content, and volatile organic compounds. For monitoring and visualization in real time, the gathered data is sent to the Thing Speak cloud platform. Reduced human error, increased grading accuracy, and a scalable, affordable solution appropriate for actual storage and procurement settings are the goals of the suggested system.</p> <p>Keywords: IoT; Raspberry Pi; Grain Quality Detection; Convolutional Neural Network (CNN); YOLOv8; Image Processing; Smart Agriculture.</p>

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Introduction

The market price, shelf life, and general usefulness of agricultural products are all directly impacted by grain quality. Grain inspection is still done by hand in many developing nations using visual inspections or minor laboratory tests. These labor-intensive, slow, and frequently human judgment-based approaches can lead to inconsistent grading and monetary losses. Automated agricultural monitoring systems are now possible thanks to recent developments in artificial intelligence (AI) and Internet of Things technologies. CNN models for YOLOv8 have demonstrated strong proficiency in recognizing visual traits like surface flaws, color variation, and grain texture. In addition, IoT sensors are able to continuously track environmental factors that affect grain spoilage and freshness. This study suggests an intelligent grain quality analysis system that combines real-time IoT sensor monitoring, CNN-based image classification, and YOLOv8. The device simultaneously records environmental parameters and takes grain photos. Every piece of data is uploaded to a cloud platform for visualization and storage. Developing a portable, affordable, and dependable solution that enhances transparency and facilitates data-driven decision-making in grain trading and storage is the primary objective. Grain quality has a significant impact on buyer confidence and storage stability. Manual observation is a common component of traditional inspection techniques, and it can differ depending on the person and the setting. Post-harvest losses and incorrect grading may arise from this discrepancy. More dependable substitutes are offered by IoT and machine learning technologies. CNN models can analyze grain images and identify defects that are hard to find by hand with YOLOv8. Grain quality is directly impacted during storage by environmental factors like temperature, humidity, moisture, and gas concentration, all of which are monitored by IoT sensors. A more thorough assessment of grain quality is obtained by combining environmental sensing with image-based analysis. Cloud platforms make it possible to track historical data and monitor remotely, which facilitates quicker and more precise storage decision-making.

Literature Review

Zhang, J., Dai, L., Huang, Z., Gong, C., Chen, J., Xie, J., & Qu, M, Corn Seed Quality Detection Based on Spectroscopy and Its Imaging Technology: A Review, 2025, This review provides an in-depth examination of non-destructive methods for evaluating corn seed quality using near-infrared spectroscopy and hyperspectral imaging. It emphasizes the advantages of integrating spectral imaging with machine learning techniques, which offer higher accuracy and reliability compared to conventional manual inspections and chemical analyses. The paper also explores key applications such as seed variety classification, vigor evaluation, internal component assessment, and mycotoxin identification, while addressing existing limitations related to system portability and real-time implementation.

Singh, A., Raj, K., Meghwar, T., & Roy, A. M, Efficient Paddy Grain Quality Assessment Approach Utilizing Affordable Sensors, 2024, This study proposes a cost-effective IoT-based system for assessing paddy grain quality by combining image processing techniques with low-cost sensors and machine learning algorithms. The system analyzes interpretable features such as grain size, shape, moisture content, and maturity level to determine quality. By reducing reliance on costly instruments and subjective manual inspection, the proposed approach enhances transparency, consistency, and fairness within agricultural procurement processes.

Pullagura, J. R., Rao, A. V. N., Kumar, P. S., Raju, M. V., & Madhavi, B., Grain Quality Analysis Using CNN and IoT Based Strategic Safeguarding, 2025, This research presents an automated grain quality assessment approach that combines a convolutional neural network (CNN) with IoT-based monitoring of storage conditions. Visual data are analyzed using image processing methods to derive morphological characteristics such as grain length and width, while sensor units continuously track environmental factors like temperature and moisture levels. The results highlight that integrating automation into the evaluation process minimizes human involvement, reduces errors, and ensures more consistent and reliable grain quality assessment.

Suhas G. K., Smart Quality Monitoring Framework for Food Grain Storage Using IoT, 2023, The framework integrates various sensors to continuously measure environmental conditions such as temperature, humidity, gas levels, and movement, helping to detect spoilage risks at an early stage. By utilizing cloud-based data monitoring and analysis, the system enhances storage management decisions and addresses large-scale inefficiencies commonly found in grain storage systems in developing nations.

Lydia, J., Vimalraj, L. S., Monisha, R., & Murugan, R., Automated Food Grain Monitoring System for Warehouse Using IoT, 2022, This study introduces a smart warehouse monitoring solution that leverages IoT-based sensors to continuously observe key environmental factors, including temperature, humidity, gas concentration, vibration, and stored grain volume. By sending live sensor data to a cloud platform through GSM connectivity, the system allows timely identification of unfavorable storage conditions, helping prevent spoilage and significantly minimize post-harvest grain losses.

Overview Of Proposed System

The reference architecture pulls hardware, software, sensors, and cloud links into one setup built to judge grain without constant human checking. At the center sits a Raspberry Pi acting as the brain for processing, communication, and control. Grain images arrive either through a small upload interface or from the attached camera, and the Pi runs them through a trained CNN that decides the quality and spits out quick preventive suggestions. The system captures grain images and performs CNN, YOLOv8 based quality classification. The sensors run their own rhythm beside the image work. A temperature-humidity unit, a moisture probe, and an MQ-135 VOC sensor track shifts that usually speed up grain decay. The Pi grabs their readings, cleans the noise, lines up the timing, and then ships everything to Thing Speak. From there, the data sits ready for charts, long-term checks, and remote decisions. An LCD screen keeps the user in the loop, showing the YOLOv8 and CNN's judgment, the current sensor numbers, and any alerts that pop up. A steady power supply protects the system from those tiny outages that ruin tests, making it easier to drop the device into a warehouse corner or a field shed without babysitting. The whole flow runs both ways: users and sensors feed the Pi; the Pi processes; the results push out to the display and to the cloud so nothing stays hidden. The design leans on modular parts, light hardware, and near-automatic behavior. People barely need to poke at it. Mixing the CNN's visual checks with IoT readings gives a fuller picture of grain condition, something closer to how farmers actually evaluate crops over time. The setup scales cleanly, and I think that makes it feel usable in real storage spaces, not just in lab writeups.

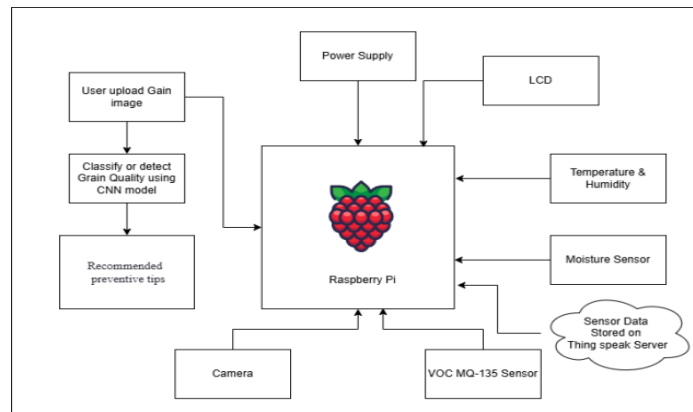


Fig.1 System Architecture

Extra pieces in the architecture kept things steadier in day-to-day use. Sensor calibration routines lived in the background so readings didn't drift and make the whole system feel sketchy. Encrypted cloud traffic guarded whatever moved through Thing Speak, and the hardware checks caught loose wiring or failing modules before they tanked a session. Scaling the setup across several warehouses or procurement sites meant keeping the design light enough that teams could clone and drop it into place without fuss. The layout leaves room to grow. Maybe later it picks up LoRaWAN for long-range links, or new optical or chemical sensors that dig deeper into grain condition. I've even seen talk about federated learning, letting each site refine the model without shipping raw data around. That idea stuck with me. All these choices push the system toward automated, cheap, portable use with smooth cross-module communication and a friendlier feel for people who don't want to wrestle with tech. And the real win comes from steady, real-time readings that actually help storage crews act before grain goes bad.

Testing And evaluation

The Smart Grain Analysis setup went through rounds of hardware, software, and performance tests to see if it could hold up in real storage settings. We broke the checks into three pieces: the image classifier, the environmental sensors, and the cloud link. Each part was tested alone first, then folded back into the full system to confirm nothing fell apart once everything ran together. For the CNN & YOLOv8, we trained and validated it on grain samples with mixed textures, odd colors, impurities, and different levels of damage. Accuracy, precision, recall, and confusion matrices showed where the model stumbled. I kept an eye on how it behaved under rough lighting, skewed camera angles, thick grain piles, and busy backgrounds. Those conditions usually break weaker models. Preprocessing tricks like contrast fixes and noise cleaning steadied the results and made the output less fussy. Sensor checks ran on a loop. We calibrated the temperature-humidity, moisture, and VOC units, then compared their readings with reference tools. We watched for drift, slow response, or spikes from environmental changes. Long-hour tests revealed how the sensors behaved when storage air shifted. Data held tight, with no packet drops or strange gaps. When we forced abnormal conditions or fake spoilage events, the alert system triggered without dragging its feet.

System-level testing looked at speed, network behavior, and the user side. Thing Speak uploads were tested under weak, middling, and stable bandwidth to see how often updates hit the cloud. The LCD screen had to be readable, quick, and clear, otherwise people would get frustrated. Power checks showed the Pi and the sensors could run nonstop without babying, good enough for warehouses or purchase centers where days blur. We also handed the device to people with no technical background. They managed to operate it, read the outputs, and trust the preventive hints the system offered. According to my notes, the simplified interface and the automated flow cut the intimidation factor. CNN, YOLOv8 model performance was evaluated using accuracy, precision, recall, and confusion matrix metrics.

Altogether, the tests showed a system that delivers real-time, accurate grain checks and scales without turning finicky. It fits storage rooms, field visits, and trade sites pretty cleanly. Future rounds might need bigger datasets, more grain types, longer stress tests, and multi-location trials so the model doesn't get too cozy with one environment.

Ethical, Legal, And Social Implications

Rolling out an AI- and IoT-driven grain assessment setup drags in a mix of ethical worries, legal rules, and social reactions that you can't ignore if you want people to actually trust the thing. The system has to stay open about what it does with grain images, sensor readings, and the final judgment it spits out. If the box feels like a black hole, farmers and traders start doubting it. I've seen that hesitation in early demos. Clear explanations and simple preventive tips help people feel like the system isn't making silent calls behind their backs. And the dataset has to be broad. Different grain types, climates, storage quirks — without that mix, the model leans toward certain samples and punishes others for no good reason.

Legal angles sneak in too. Even though the data isn't personal, storage numbers and quality ratings still matter in trade. Mishandled data can sway prices or leak competitive info. So, encryption and locked-down access matter more than people assume. Regional data rules differ, and the system has to play by them. Another messy bit is responsibility. If the system misreads a batch and someone loses money, who steps up? The developer? The operator? The warehouse manager? That question hangs in the air until someone puts it in writing. Social shifts hit hardest. Automated grading can brighten things by cutting bias, smoothing pricing, and helping small farmers who don't have lab access. At the same time, folks who work in manual inspection sometimes read it as a threat to their job. Training sessions, local demos, and folding the tool into existing work patterns soften that tension. Costs matter, maybe more than anything. If the system becomes pricey, the tech will sit with large buyers and leave small farmers stuck, widening a gap that's already too wide.

There's an environmental angle too. Sensors and boards wear out, and the waste piles up if the design isn't repairable or recyclable. Low-power hardware cuts some guilt, and making parts replaceable instead of disposable helps. In the end, the system's long-term acceptance rests not only on how sharp the models are but on how people feel using it. Fairness, access, trust — those pieces determine whether the tech becomes part of everyday grain handling or stays a shiny lab project.

Discussion

The development and testing of the Smart Grain Analysis setup show how AI image work and IoT sensing can mesh to update grain grading in a pretty real way. The tests made it clear that pairing CNN-based visual checks with live environmental readings gives a fuller picture than either stream alone. The mix cuts the guesswork that creeps into manual grading and pushes decisions toward numbers instead of gut calls during storage, buying, and selling. I've seen traders argue for hours over tiny imperfections; this system trims that noise. Running everything on the edge brings its own perks. The Raspberry Pi handles inference without leaning on fast internet, which cuts lag and keeps privacy tighter. It also dodges cloud-compute fees, keeping costs low enough for small farms that already stretch budgets thin. Cloud links still matter for long-term charts, remote oversight, and building a traceable story of how grain behaved over weeks. That history becomes handy when storage conditions wobble.

Some snags linger. CNN & YOLOv8 results wobble when the lighting turns sloppy, or when the camera slips out of focus, or when the grains form uneven piles. Training data can only go so far; widening the dataset across regions, crop types, and storage quirks should steady the model. Sensors drift over time too, and calibration cycles become one of those chores you can't skip. Rural connectivity flickers, so cloud updates may lag, though the Pi keeps the system running even when the network takes a nap. [4] User reactions leaned positive. People liked the small size, the nearly hands-off workflow, and the way the results popped up without technical digging. But long-term success hangs on price staying low, local institutions backing the rollout, and the system fitting into what storage centers already do. Linking with cooperatives, ag offices, and procurement hubs could push adoption faster and build trust that numbers aren't rigged. [5] The setup shows real promise for making grain grading more open, faster, and fair for buyers and sellers. Its modular build leaves room for new grain types, tougher deep-learning models, spoilage prediction, or bigger sensor sets. Keeping the system grounded through field trials, steady

user feedback, and slow, careful iteration will shape how far it spreads and how much change it can actually make. The results show that combining CNN, YOLOv8 based image analysis with IoT sensing improves grain quality assessment accuracy.

Conclusion And Future Scope

By combining CNN and YOLOv8-based image processing with Internet of Things-based environmental sensing, the suggested smart grain analysis system shows an effective method for automated grain quality monitoring. Through the analysis of both visual grain characteristics and storage environmental parameters like temperature, humidity, moisture, and gas levels, the system allows for real-time monitoring of grain condition. Deployment in low-resource agricultural environments is made possible by the utilization of Raspberry Pi as an edge computing device, which also minimizes processing latency and cloud dependency.

This solution enables improved consistency of grading within an organization, decreases the likelihood of human error when doing visual inspections on product quality; provides a cost-effective way to monitor stored grains and evaluate agricultural quality. This includes the use of real-time monitoring together with data visualization to enable more effective decision making about both how grains are stored and bought. Therefore, as a comprehensive solution gives organizations the capability to create viable smart agricultural systems, and accelerate the adoption of artificial intelligence and internet of things within real world farming applications.

Future success can lead to a larger dataset by having many varieties of grain present, with different storage methods for varying parts of the world, making the model more robust and providing accurate results. Future work could include testing and implementation of new advanced deep learning models to enhance the ability of the model to detect and identify bad grain with the lowest computational costs possible. The inclusion of additional sensors such as CO₂ sensors, pest detection sensors and sensors for monitoring microorganisms may help create deeper grain quality assessments. The system can also provide users with the ability to connect to mobile applications for alerts, and provide remote access for monitoring purposes.

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