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AI and digital tools in seed testing and quality assurance: A review

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Abstract

This article explores the transformative impact of Artificial Intelligence (AI) and digital technologies in seed testing and quality assurance. It discusses key applications such as automated seed sorting, disease detection, moisture analysis, viability assessment and supply chain management. The integration of AI and digital tools is shown to enhance speed, accuracy and objectivity in seed quality assessments, offering benefits like early issue detection, cost reduction and global standardization. Challenges includes high initial investment, the need for skilled personnel and data security concerns are addressed, along with future prospects for fully automated labs and climate change resilience prediction. The importance of collaboration among researchers, technologists, policymakers and the seed industry are emphasized to responsibly advance agricultural productivity and sustainability.

Keywords: Artificial Intelligence (AI), digital tools, seed testing, quality assurance, automation and machine/deep learning, hyperspectral imaging, seed sorting, disease detection, viability assessment

1. Introduction

High-quality seeds are the foundation of successful agriculture, directly influencing crop productivity, food security and sustainable farming practices. Traditional seed testing methods, while reliable, are often time-consuming, labour-intensive and subject to human error. As global demand for food increases and agricultural practices become more technology-driven, there is an urgent need for faster, more accurate and standardized approaches to seed quality evaluation. (Raghavan *et al.*, 2024; Srinivasaiah *et al.*, 2023) ^[14, 17].

The emergence of Artificial Intelligence (AI) and digital tools is revolutionizing the field of seed testing and quality assurance. Advanced technologies such as machine vision, deep learning models, hyperspectral imaging, blockchain systems and automated diagnostic platforms are transforming traditional practices, offering unprecedented levels of speed, precision and objectivity. These innovations not only streamline seed quality assessments but also enhance traceability, promote transparency in the seed supply chain and contribute to global efforts toward harmonized seed standards. (Granitto *et al.*, 2005; Tu *et al.*, 2018) ^[8, 19].

This article explores the transformative impact of AI and digital technologies in seed testing. It highlights key applications, including automated seed sorting, disease detection, moisture analysis, viability assessment and supply chain management. It also discusses the benefits, challenges and future prospects of integrating these technologies, emphasizing the need for collaboration among researchers, technologists, policymakers and the seed industry to fully harness the potential of AI for advancing agricultural productivity and sustainability.

2. Applications of AI and Digital Tools in Seed Testing

2.1 Automated Seed Sorting and Grading

Advanced imaging systems capture detailed visual data on seed samples, while machine learning algorithms are trained to detect and classify impurities based on various features such as shape, texture, colour and size. Machine learning algorithms are used to train the system with an image dataset and the system will come up with model deployment to be used in the testing phase.

During the testing phase (Figure 1), the camera detects and captures images different from of items and then classifies them using a computer vision algorithm. The items received are graded via a computer vision using an estimated size and shape analysis algorithm into different grades. The image is converted into a grey image where the filter is

applied to extract the parameter most closely related to the item’s information. Then, the number of pixels ranging from 0 to 255 in the converted grey image is counted to calculate the image threshold. Then, the proposed system sends the results of item grading to the sorter (Figure 2), where the items are sorted based on the type and grade (Dewi *et al.*, 2024) ^[4].



Fig 1: A proposed overview of smart fruit selection and grading system using a machine learning approach (Source: Dewi *et al.*, 2024) ^[4]

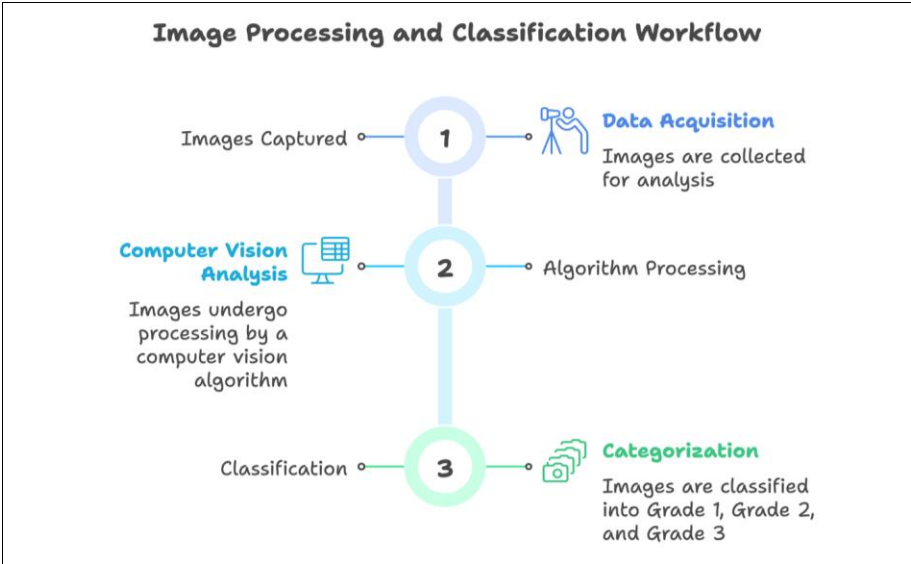


Fig 2: Proposed prototype system flowchart (Source: Dewi *et al.*, 2024) ^[4]

2.2 Germination Testing

Many computer-aided systems have been developed to evaluate seed germination rate based on seed area and seedling length. In order to increase the throughput of germination testing, (Chao Li *et al.*, 2012) ^[13], presented an approach that differentiates germinated seeds from non-germinated ones based on changes in seed length and area. In this approach, image analysis of seed images captured at regular predefined interval is done. This approach used Canny edge detection as well as Hough line transform to separate seeds from coloured background, then distance transform is done to find skeletons of seed and finally chamber (Figure 3).

The camera was mounted outside the germination chamber and was covered with black fabric to eliminate ambient light. The images of germinated seeds were acquired after 1 hour interval in order to monitor the growth rate of each seed. After image acquisition, these images were processed by using image processing software for root length calculation. This system was tested for seed samples of lettuce (*Lactuca sativa*) and sorghum (*Sorghum bicolor*). In each test, three runs of 10 seeds each were conducted. Images were collected every hour and saved to the hard disk over the entire test. Each test was conducted for 144 hours. The results showed for the lettuce test, the overall average error was -0.13 cm with a standard deviation of 0.08 and for sorghum, the overall average error was -0.07 cm with a standard deviation of 0.08. The errors between manual and machine vision measurement were very small hence this can be used to estimate seed vigour.

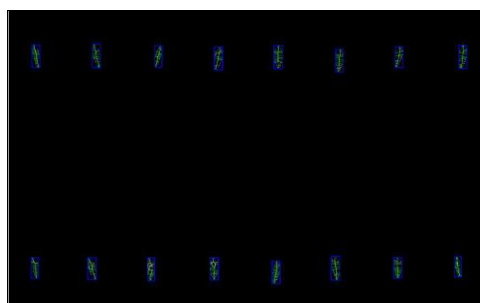


Fig 3: Extracted seed skeletons enclosed with minimum bounding box. (Source: Chao Li *et al.*, 2012) ^[13]

Seed Health Testing

Seed health testing is a critical step in ensuring the production and distribution of disease-free seeds, directly impacting crop health and yield. Recent advancements in AI-powered diagnostic tools have greatly improved the detection of seed-borne pathogens. These tools use trained algorithms to analyse seed images and biological data, allowing for rapid and highly sensitive identification of fungal, bacterial and viral infections. AI models can recognize patterns and anomalies that might be difficult for human inspectors to detect, making the diagnostic process more accurate and consistent. (Kusumaningrum *et al.*, 2018) ^[12].

In addition to AI diagnostics, machine vision and spectroscopy technologies are being increasingly applied for disease identification in seeds. Machine vision systems, equipped with high-resolution cameras, capture detailed images of seeds to spot visual symptoms of disease, such as discolouration, deformities or lesions. Meanwhile, spectroscopy techniques, including near-infrared (NIR) and hyperspectral imaging, analyse the chemical composition of seeds to detect internal infections that may not be visible externally. Together, these technologies enable early and non-destructive detection of seed-borne diseases, greatly

enhancing the reliability and efficiency of seed health testing.

Some examples are: fluorescence imaging, multispectral or hyperspectral imaging, infrared spectroscopy, fluorescence spectroscopy, visible/multiband spectroscopy and nuclear magnetic resonance (NMR) spectroscopy reviewed multiple methods (sensors and algorithms) for pathogen detection, with special emphasis on postharvest diseases.

Fluorescence spectroscopy refers to a type of spectroscopic method, where the fluorescence from the object of interest is measured after excitation with a beam of light (usually ultraviolet spectra) (Belasque *et al.*, 2008) ^[11].

In fluorescence imaging the change in blue-green fluorescence and chlorophyll fluorescence of the plants upon ultraviolet excitation could provide the status of physiological condition of the plant (Gamerio *et al.*, 2014) ^[7].

2.3 Moisture content analysis

Traditional moisture testing methods are often time-consuming and can be destructive. Recent innovations have introduced digital moisture meters integrated with AI, offering a faster, non-destructive and highly precise alternative. These advanced devices use sensors to measure the electrical properties or dielectric constant of seeds, which are closely related to moisture levels. AI algorithms then analyse the collected data, automatically correcting for variables like seed type, size and environmental conditions, thus ensuring more consistent and reliable readings.

A digital moisture meter equipped with AI, such as the *Grain Sense Analyzer*, is used to assess the moisture content of wheat seeds during storage. The device scans the seeds using near-infrared (NIR) sensors and instantly measures their moisture levels without damaging them. The built-in AI algorithm adjusts the readings based on the seed variety and ambient conditions, providing highly accurate results within seconds. Over time, as more data is collected, the device fine-tunes its models to further enhance precision. This allows farmers and seed companies to monitor seed quality in real-time, ensuring optimal storage conditions and reducing the risk of spoilage. (Huber and Jankala, 2020) ^[11].

The Perten Instruments DA 7250 NIR Analyser works on the principle of near-infrared (NIR) reflectance spectroscopy. When seeds are exposed to NIR light, specific wavelengths are absorbed based on their moisture, protein, oil and carbohydrate content. The analyser captures the reflected light and using pre-calibrated AI models, interprets the spectral data to rapidly predict moisture and other seed properties. Its non-destructive design allows for instant, accurate measurements without sample preparation, making it highly efficient for seed quality assurance and processing.

2.4 Seed Viability and Vigour Testing

Seed viability and vigour are essential parameters that determine the ability of seeds to germinate successfully and produce strong, uniform seedlings under a range of environmental conditions. Conventional methods for assessing these traits, such as standard germination tests, tetrazolium staining and accelerated aging tests, though reliable, are often laborious, time-intensive and partially destructive. The emergence of deep learning models, integrated with advanced imaging techniques and biochemical marker analysis, has brought a transformative shift to seed viability and vigour testing.

Deep learning models, particularly convolutional neural networks (CNNs), are capable of analysing thousands of seed images to identify subtle patterns linked to vigour traits that are

invisible to the human eye. These models are trained using large datasets where images of seeds are labelled according to their known vigour and viability outcomes. Over time, the AI system learns to predict seed performance based on visual cues such as surface texture, colour variation, morphological deformities and size anomalies. In addition, by incorporating biochemical markers such as enzyme activity or antioxidant levels into the models, researchers can improve the prediction accuracy even further, providing a comprehensive, non-destructive evaluation of seed quality. (Bhurtel *et al.*, 2019) ^[2].

Working model of CNN: The process begins by feeding seed images into the CNN, where the model automatically learns important visual features without manual intervention. Convolutional layers apply filters across the image to detect local patterns such as edges, textures, or colour variations, which in seed analysis may correspond to cracks, disease symptoms, or shape anomalies. Following convolution, an activation function like ReLU introduces non-linearity, enabling the network to capture complex relationships in the data. Pooling layers then down sample the feature maps to reduce computation and emphasize the most prominent features. These extracted features are flattened and passed through fully connected layers that interpret the information and make predictions, such as classifying seeds by species, assessing their vigour, or identifying defective seeds. Finally, the output layer provides a classification label or probability score. CNNs thus offer a highly accurate, automated solution for enhancing seed testing processes, including germination prediction, disease detection, and sorting, by analysing intricate visual traits efficiently. Moreover, hyperspectral imaging combined with AI presents another powerful tool for internal seed quality assessment. Hyperspectral imaging captures both spatial and spectral information across a wide range of wavelengths, far beyond the visible spectrum. This allows the detection of internal physiological and biochemical changes within seeds that are early indicators of deterioration, loss of viability, or reduced vigour long before any external symptoms appear. AI algorithms process the vast amount of spectral data to differentiate between viable and non-viable seeds based on specific biochemical signatures, such as moisture distribution, lipid peroxidation and metabolic content.

3. Digital Tools Supporting Quality Assurance

3.1 Blockchain Technology

Blockchain technology is emerging as a powerful digital tool to strengthen quality assurance systems in the seed industry, by providing a decentralized and tamper-proof ledger, blockchain ensures traceability, transparency and trust across every stage of the seed supply chain from breeding and production to certification, distribution and sale.

Through blockchain platforms, each transaction involving seed lots such as planting, harvesting, quality testing and storage can be recorded with a timestamp and made accessible to all stakeholders. This immutable record allows seed companies, farmers, certifying agencies, and consumers to verify the origin, genetic purity, quality tests and handling history of seeds in real-time. For instance, farmers can scan a QR code on a seed packet to view the complete journey of the seeds, including their breeder source, germination percentage, disease-free certification and storage conditions.

A practical example of blockchain in seed supply chains is the *SeedX* platform, which uses blockchain to document and validate seed certification and quality assurance processes.

Similarly, *AgriLedger* has piloted blockchain solutions to enhance seed traceability among smallholder farmers, ensuring that only certified and high-quality seeds reach the end users. By reducing fraud, counterfeiting and mislabelling of seeds, blockchain fosters greater confidence in seed markets, promotes regulatory compliance and ultimately supports agricultural sustainability and food security.

As digital agriculture evolves, the integration of blockchain with other technologies like IoT (Internet of Things) and AI is expected to further enhance seed quality assurance systems by offering automated monitoring, real-time data collection and predictive analytics, making the seed supply chain smarter and more resilient.

4. Benefits

The integration of AI and digital tools into seed testing and quality assurance systems brings a wide array of benefits that are reshaping the seed industry:

4.1 Increased Speed and Efficiency in Testing

Traditional seed testing methods are often labour-intensive and time-consuming. AI-powered imaging, machine vision and deep learning algorithms can rapidly process thousands of seed samples, delivering results within minutes. This acceleration helps breeders, seed companies and farmers make faster, data-driven decisions, ultimately reducing the time to market.

4.2 Higher Accuracy and Objectivity

Manual testing is susceptible to human error and subjective biases. AI and machine learning models standardize evaluations by detecting subtle variations in seed size, shape, colour, internal structure and biochemical markers with high precision. This leads to more consistent, reproducible and unbiased seed quality assessments.

4.3 Early Detection of Issues Leading to Better Crop Establishment

Advanced imaging and spectroscopy techniques, combined with AI analytics, enable the early detection of seed-borne diseases, physiological disorders and vigour loss. Identifying these issues before planting helps in selecting the best seed lots, improving germination rates, uniformity and ultimately leading to stronger crop establishment and higher yields.

4.4 Cost Reduction in the Long Term

Although initial investments in AI systems and digital tools can be significant, they greatly reduce operational costs over time. Automation decreases the need for extensive manual labour, minimizes losses due to poor-quality seeds and enhances resource efficiency in breeding and production programs.

4.5 Standardization and Global Harmonization of Seed Quality Standards

Digital tools provide standardized, automated and globally replicable protocols for seed testing. This supports international trade by ensuring that seed quality assessments meet recognized benchmarks across countries, promoting transparency, trust and regulatory compliance in global seed markets.

5. Challenges and Limitations

Despite the transformative benefits of AI and digital tools in seed testing and quality assurance, several challenges and limitations remain:

5.1 High Initial Investment in Technology

The adoption of advanced AI systems, hyperspectral imaging devices and blockchain infrastructure requires substantial upfront capital. For many small- and medium-sized seed enterprises, this investment can be prohibitive, limiting widespread deployment (Dadlani and Narendra 2025) ^[3].

5.2 Need for Skilled Personnel to Operate and Interpret AI Outputs

AI systems, though automated, still require skilled operators and analysts who can manage the technologies, interpret results correctly and maintain systems. A shortage of trained personnel can create bottlenecks in adopting these innovations efficiently. (Dharmaraj and Vijayanand 2018) ^[5].

5.3 Data Privacy and Cybersecurity Concerns

As seed quality data and supply chain information become digitized and stored on cloud-based platforms or blockchain networks, concerns about data breaches, unauthorized access and cybersecurity risks arise. Ensuring robust data protection measures is critical to maintain trust among stakeholders.

5.4 Calibration and Validation of AI Models Across Different Species and Environments

AI models trained on specific crops or environmental conditions may not perform well when applied to different species or geographical areas. Continuous calibration and validation across diverse datasets are necessary to maintain model accuracy and relevance (Dharmaraj and Vijayanand 2018) ^[5].

6. Future Prospects

The future of AI and digital tools in seed testing is highly promising, with ongoing innovations likely to further revolutionize the field:

6.1 Integration of AI with Robotics for Fully Automated Seed Testing Labs

Combining AI with robotics and Internet of Things (IoT) technologies can lead to the development of fully automated seed testing laboratories, capable of operating 24/7 with minimal human intervention, enhancing productivity and reducing operational costs (Srinivasaiah *et al.*, 2023) ^[17].

6.2 Development of AI Models for Predicting Seed Performance under Climate Change Scenarios

With increasing climate variability, new AI models are being developed to predict how seeds will perform under different stress conditions such as drought, salinity, and extreme temperatures, enabling breeders and farmers to select resilient varieties (Li *et al.*, 2012) ^[13].

6.3 Personalized Seed Recommendations to Farmers Based on AI Analysis

By integrating farm-specific data (e.g., soil health, weather patterns, historical yields) with seed quality parameters, AI systems can offer customized seed recommendations to farmers, helping optimize crop performance and resource use (Vanitha *et al.*, 2023) ^[20].

7. Conclusion

The integration of AI and digital tools is fundamentally transforming the landscape of seed testing and quality assurance. Techniques such as AI-powered imaging, machine learning, blockchain, hyperspectral analysis and digital moisture sensing

have significantly increased the speed, accuracy, and objectivity of traditional seed testing methods (Suresh *et al.*, 2023) ^[18]. These innovations not only enhance physical and physiological seed evaluations but also facilitate early detection of seed-borne diseases, better traceability and global standardization of seed quality standards (Ducournau *et al.*, 2005) ^[6]. However, to fully realize the potential of these technologies, there is a pressing need for collaboration among researchers, technologists, seed companies and regulatory bodies. Collaborative efforts are essential to address challenges related to high costs, skill gaps, data security and model calibration across diverse crops and environments. Finally, while embracing AI-driven advancements, it is crucial to promote the responsible, ethical, and inclusive use of these technologies. Ensuring that smallholder farmers, especially in developing regions, can access and benefit from digital innovations will be key to achieving sustainable agricultural growth and global food security. A balanced approach that combines technological progress with social inclusivity will define the next era of seed quality assurance.

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